Algorithmic Trading, COMP0051, 2023/24

Coursework 2.

Introduction

This work introduces Algorithm Trading strategies to generate money from estimating on SPTL funds which tracks the long-term Treasury bonds. As per [1] Algorithmic trading involves using computer algorithms to execute trading strategies. These algorithms, often fuelled by vast amounts of market data and statistical models, make split-second decisions on buying or selling financial instruments. By using historical data from 2014 to 2019, it is examined how various organizations can use their initial capital and gross limit (book size) to explore opportunities for maximizing profits. This work has established how well the strategies contribute and how possible the risks are. It has also looked at the different implications of an interest rate change. For this work we determine concepts such as the daily profit, turnover, and the drawdown (being the losses from peak to trough), thus, we shape our way of managing risks and of improving returns. We have adopted a simple price-performance metrics like the Sharpe Ratios to gauge performance and the strategies of risk management will be discussed based on the variations in the market fluctuations. This report critically analyses strategies for investors to make smart decisions regarding ETFs, such as SPTL. It explores various approaches and techniques for optimizing investment decisions and maximizing returns in the context of leveraged ETFs.

Methodology

Time Series Prep

The first step of the task was to initiate the data collection phase, and for this purpose, the price data was extracted from Yahoo Financial using API for the SPTL ETF. Meanwhile, the Effective Fed Funds Rate (EFFR) data was also accessed, which can be found on the New York Federal Reserve website. The Python Pandas package was applied to process and deal with the acquired data in a manner of efficiency. At first, it was made sure both datasets were cleaned and the date columns were properly formatted so they could easily align for further manipulations.

Secondly, these two SPTL and EFFR datasets were merged by their dates as the corresponding ones. Applying an inner join method has proven to be an efficient tool to eliminate any unnecessary data points and ensures data alignment which eliminates the violation of data integrity. Then we moved on to compute the daily risk-free rate. Applying the standard year-day convention trading days per year of 252, divided the cost of money risk-free rate by 252 to have the daily risk-free rate, this is consistent with SPTL ETF's daily pricing.

In the next stage, excess return with SPTL ETF per unit of the dataset the day was calculated using the following formula:

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

Formula taken form provide coursework

Where:

- r_t^e is the expected return at time *t*.
- Δp_t represents the change in price at time *t*.
- p_t is the price at time *t*.
- r_t^f is the risk-free rate of return at time *t*.

```
         Date       Open       High        Low   Close  Adj Close  Volume  \
0 2014-01-02  29.924999  30.070000  29.924999  30.055  23.299061   25400
1 2014-01-03  29.959999  30.105000  29.959999  30.035  23.283543   22000
2 2014-01-06  30.110001  30.270000  30.110001  30.160  23.380444    3200
3 2014-01-07  30.240000  30.260000  30.200001  30.260  23.457972    3800
4 2014-01-08  30.075001  30.184999  30.075001  30.150  23.372686   14800

   Daily Returns  Volatility  Rate (%)        rf       rte
0       0.000000    0.000000      0.08  0.000317 -0.000317
1      -0.000665    0.000471      0.08  0.000317 -0.000983
2       0.004162    0.002616      0.08  0.000317  0.003844
3       0.003316    0.002391      0.07  0.000278  0.003038
4      -0.003635    0.003160      0.07  0.000278 -0.003913
Data processed successfully.
```

Fig 1 – Glance of SPTL data with calculated variables as per above formula

The SPTL time series, the Effective Fed Funds Rate (EFFR), and the excess return per unit SPTL were plotted using Python implementation of the Matplotlib library and the time period of the analysis is from 1-1-2014 to the 31-12-2019. SPTL excess return and EFFR were given appropriate sizes and plotted against the date which was gathered from the merged data set. Each series was assigned a distinct colour: blue denotes SPTL excess return, green denotes EFFR, and red indicates the risk-free rate. It helps with comparison.

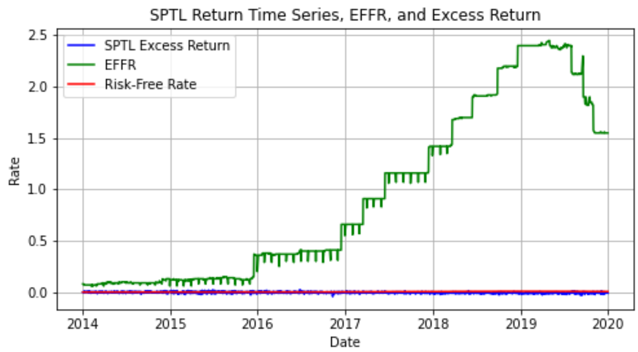

Fig 2 – Plot of SPTL Excess Return, EFFR and Risk-free rate

The EFFR and risk-free rate lines appear to be horizontal, suggesting continuity of interest rates within a specific timeframe. In contrast, the SPTL Excess Return, which is calculated as the return of SPTL minus the risk-free rate, shows large upward spikes at different levels, which implies periods of outperforming the risk-free rate. In addition, there are plateaus where the excess return is not changing, possibly pointing out when SPTL had similar returns as a risk-free rate. These results show that the SPTL investment returned consistently greater than the risk-free rate, regardless of whether the EFFR was used as a benchmark rate or a reference to the general interest rate. That might mean SPTL has had good performance over the period under review.

Trading Strategies

In a leveraged strategy, the concept of "leverage book size" becomes especially important, since it shows the total value of the assets that an investor can control. Utilizing leverage allows the investor to multiply their capital by a set amount thereby boosting potential returns or losses. This method involves a sequence of following the money of assets, the SPTL ETF, traded over time. These trades could be either long or short, so investors can use them for both upward and downward movements of the price. The leveraged book size at any instance of time is calculated by multiplying the initial capital denoted by V_0 by the leverage factor L. Additionally, it is essential to note that in a leveraged strategy, the sequence of dollar values θ_t are adheres to the following condition:

$$|\theta_t| \leq V_0 \cdot L$$

Under such a condition, the amount of the trade will not be much rather stay below the border as defined by the leverage and the initial capital of the investor. This equation, in general terms, portrays the total value of the position up V_0 x L, which arose from the initial capital of V_0 multiplied by a leverage L. Therefore, even after a loss in the initial position size, a trader can continue to trade with a fixed maximum position size, which is derived from the maximum allowed capital loss.

For the SPTL ETF, three different leveraged trading strategies are outlined, each of them starting with $200,000 in capital and using a 10 leverage. All these strategies, the Trend Trading Strategy, Momentum Strategy, and Mean-Reverting Strategy, are focused on searching for a particular type of situation in the market. The dataset is arbitrarily divided into a training set of 70% and a test set of 30%, so the trading performance of the strategy can be evaluated.

With the formula shown below of excess return each day, the PnL (profit and loss) of each strategy is computed depending on the size of the SPTL hold, which in turn affects the PnL.

$$\Delta V_t = \left(\frac{\Delta p_t}{p_t} - r_t^f\right)\theta_t$$

Formula taken form provide coursework

Where:

ΔV_t daily trading profit and loss (PnL) for each strategy.

Δp_t represents the change in price at time t.

p_t is the price at time t.

r_t^f is the risk-free rate of return at time *t*.

θ_t is the dollar value of the SPTL ETF held in the trading portfolio at time *t*.

With the implementation of these strategies together with performance analysis, the investor would be able to realize which of them works best in the art of making profit from market trends and capturing winning margins.

Trend Following Strategy

Trend following is a strategy that involves capturing gains by looking at an asset's momentum when it's moving in one specific direction, whether it's up, down or sideways. You can think of trend trading as taking the path of least resistance that is if the market is rising, you would take a long position and if it is falling, you would go short.

The implementation process of the trend-following trading strategy is with the logic that the excess return is obtained by applying the formula shown below.

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

Formula taken form provide coursework

The core of the strategy is the trend-following logic, which is where positions are modified respectively considering whether the current closing price is higher, lower, or equal to the previous day's price. Profit and loss are determined by calculating the excess return multiplied by the size of the investment.

p_t ((Current closing price)> p_{t-1}((Previous day's closing price) – 'Buy'

p_t ((Current closing price) < p_{t-1}((Previous day's closing price) – 'Sell'

otherwise – 'Hold'

The PnL is determined by multiplying the excess return with the position size. The positions are incremented and decremented by initial capital. This makes sure that the value of the position always remains within the given gross limit *(*V_0 x *L)*.

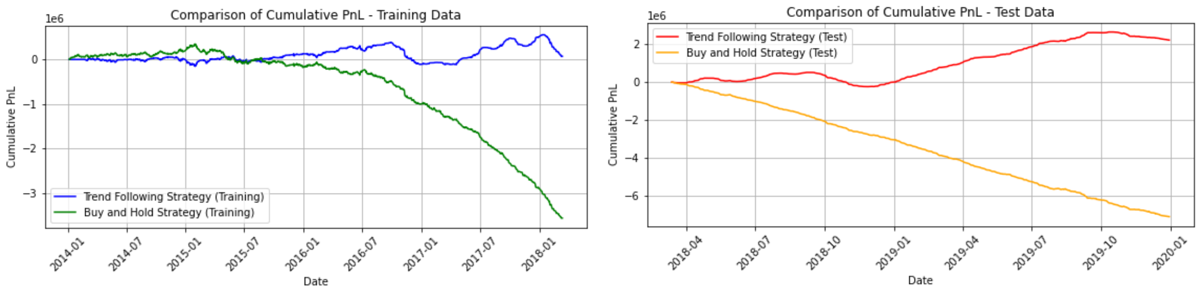

Fig 3 – Comparison of Trade following strategy with Buy and hold strategy for both train and test set.

The comparison plot Trend Following trading strategy with the baseline strategy buy and hold is shown above for two sets of data, training data, and test data. The trend following strategy (blue line) in the training data is seen to be slightly profitable whereas, the buy and hold strategy (green line) is in a downward trend which points to losses over time. On the test data graph, the following trend is observed in the trend-following strategy (red line), which exhibits significant growth, and remarkable profits. Buy and hold (yellow line) decreases at a much slower rate. So, there is a clear domination of the trend-following strategy as compared to the buy-and-hold approach in both training and test periods. The trend-following approach claims significantly higher gains than the passive approach of buy-and-hold.

Momentum Trading Strategy

According to [2] Momentum means the speed of the price variation of a security with which new price is being formed, i.e. the rate of acceleration of price change. Momentum trading strategy involves trying to use this momentum as you receive more evidence that a trend is increasing. This technique has the objective of being able to catch the upwards or downwards trend and using this momentum of the trend strategy is developed to get the profit from it. In simple terms, momentum trading is like catching a moving train at just the right moment to speed up your gains.

The implementation of this momentum trading strategy is based on a historical price of the SPTL ETF which is also the aim of capturing the momentum-driven market moves. The strategy is implemented through a Python script using the Pandas library for data manipulations. The data set is loaded and pre-processed, with the initial capital (V0) and the leverage (L) defined for the leveraged book size calculating which is the total value of assets controlled. According to research conducted [3] Investment methods that in the momentum return signal exhibit significantly high returns and the Sharpe ratios in contrast to time series momentum and other benchmark strategies. In the final analysis, the resultant outcome is that return signals help an investor to be effective during estimating and hedging thus projects a reliable strategy which is good for improving investment results. So, the excess return is calculated by subtracting the closing prices from the risk-free rate by the formula below as discussed above.

The strategy begins with taking a position and a signal with the momentum from the first data point continuing until it is time to reset and work with the test dataset. The strategy works with the logic that when for each data point, it determines whether the excess return is positive or negative. If it has a positive influence on it, it buys more assets adding the initial capital (V_0) to the initial position size. If the excess return is negative, it sells some assets thereby, decreasing the position size by subtracting the initial capital from the previous position size. If the excess return is zero, the position size stays the same. Such a process allows for adjustment of the portfolio size relative to the performance of the investment, which helps to regulate risk and improve returns as time goes on. The implementation ensures that the value of the position always remains within the prescribed gross limit (V_0 x L).

$$\textit{Excess Return} > 0 - \text{'Buy'}$$

$$\textit{Excess Return} < 0 - \text{'Sell'}$$

$$\text{otherwise} - \text{'Hold'}$$

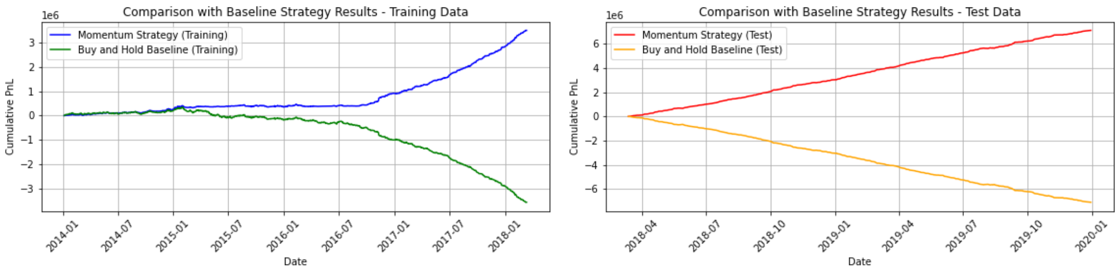

Fig 4 – Comparison of Momentum strategy with Buy and hold strategy for both training and test set.

The comparison plot momentum trading strategy with the baseline strategy buy and hold is shown above. The momentum trading strategy has better results than the buy and hold strategy according to training data and test data. The momentum technique's performance (blue line) can be observed to exceed that of the buy and hold strategy (green line) consistently in the training data plot, with better cumulative profit and loss (P&L). On the contrary, in the data of the test phase, both systems show profits. But, the momentum strategy (red line) displays higher profits, which is maintained at an upward trend of cumulative P&L unlike the buy and hold strategy (yellow line). In the long run, the momentum strategy shows a superior level of performance under both datasets.

Mean Reverting Strategies (Moving average approach)

According to [4] the mean reversion idea is the basis of many trading techniques where you perform buying and selling of those asset classes that have moved away from their average values. It is assumed that in the longer term, the prices here will return to the average price level and follow the traditional price pattern.

The mean reversion trading strategy applies a rolling average to detect potential market reversals and make trading choices in line with this detection. The mean reverting strategy is implemented with the logic that the difference between consecutive closing prices and the risk-free rate was found to figure out how much extra return we could potentially get. The trading plan begins where each data point in the strategy is compared with the 30-day rolling average of its closing prices. When the current price is higher than the rolling average, it means the market might be overvalued, so the strategy sells stocks expecting the prices to fall back to normal. On the other hand, if the current price drops below the rolling average, it suggests the market might be undervalued, so the strategy buys more stocks expecting the prices to go up again. Otherwise, it maintains the previous position. The positions are incremented and decremented by initial capital. This makes sure that the value of the position always remains within the prescribed gross limit (V_0 x L).

$$p_t \text{ ((Current closing price)} > \text{rolling moving average} - \text{'Sell'}$$

$$p_t \text{ (Current closing price)} < \text{rolling moving average} - \text{'Buy'}$$

$$\text{otherwise} - \text{'Hold'}$$

The PnL is determined by multiplying the excess return with the position size.

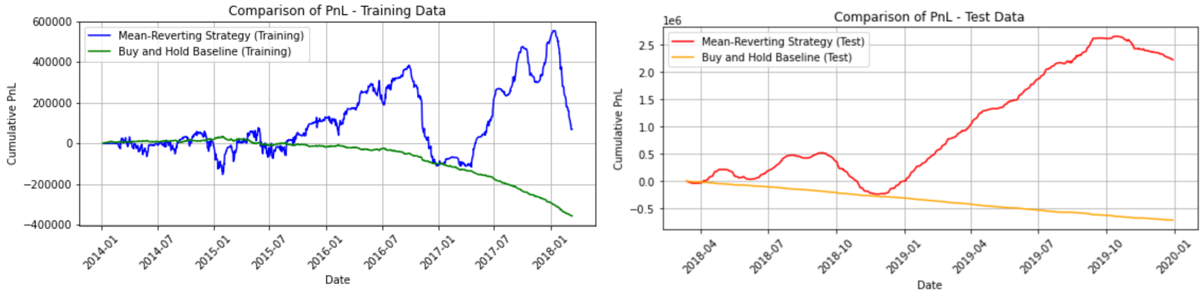

Fig 5 – Comparison of Mean Reverting Strategy with Buy and hold strategy for both training and test set.

The comparison plot Mean reverting trading strategy with the baseline strategy buy and hold is shown above for two sets of data, training data, and test data. In the chart with training data, it is observed that the mean reversion scheme (blue line) bears high volatility with high profit followed by loss, while the buy and hold strategy results in slow P&L decline which means the loss overtime. As represented by the test data plot, the mean-reverting strategy (red line) consists of volatility in the beginning but eventually ends higher on the cumulative P&L, which would make profits over the period, while the buy-and-hold strategy (yellow line) is relatively flat with little gains or losses. Mean reversion is a profitable and unstable method of investing over the test period, whereas the buy and hold is stable but produces a limited return.

Plot of all the strategies position θ_t together with upper bound and lower bound is shown below to get a view of how the position value changes as per the time period.

The upper bound is V_0 x L and lower bound is $-V_0$ x L is plotted so we can see that the θ_t does not go above and below the bounds.

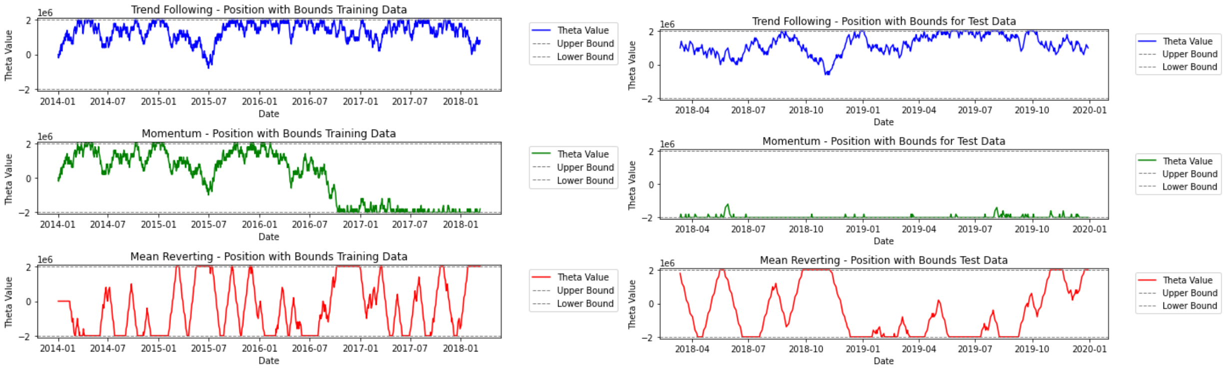

Fig 6 – Plot of θ_t positions of all the strategies together for both training and test set

The trading strategies position θ_t of Trend Following, Momentum, and Mean Reverting shown in the figures shows their position based on both training and test datasets. The Trend Following strategy, characterized by the assumption that securities will continue in their existing trend, displays a stable θ_t value within its bounds across both datasets, implying consistency rather than significant movement. The Momentum method, which sticks to the principle of trends, like the θ_t value for the train dataset, though with less variability than the test dataset because the phase of testing data was most probably more stable or less volatile. On the other hand, the Mean Reverting strategy, which utilizes the idea that prices will eventually go back to the mean level, leads to a situation where the oscillations are large and they revert to the mean as quickly as possible, showing the ability of the model to handle the training and the real-world situations.

To do deeper analysis we decide to find the turnover. The turnover in dollar value traded over time is calculated by summing the absolute changes in the position (θ_t) at each time step. Each change in position is taken in absolute terms to ensure that all trades, whether buying or selling, are summed positively, reflecting total activity without netting out opposing transactions.

$$\text{Turnover}_{\text{dollars}} = \sum_{0}^{T} |\Delta\theta_t|.$$

Formula taken form provide coursework

$|\Delta\theta_t|$ Represents change in position from time t to $t+1$.

The turnover in number of traded units is also calculated by summing the changes in position relative to the price at each time step.

$$\text{Turnover}_{\text{units}} = \sum_{0}^{T} \left|\frac{\theta_{t+1}}{p_{t+1}} - \frac{\theta_t}{p_t}\right|$$

Formula taken form provide coursework

p_t is the price at time t.

θ_t is the dollar value of the SPTL ETF held in the trading portfolio at time t

θ_{t+1} is the dollar value of the SPTL ETF held in the trading portfolio at time $t+1$.

p_{t+1} is the price at time $t+1$.

This formula considers the price of the asset, thereby normalizing turnover by the asset's value. This is important as it measures the actual quantity of assets traded, which is crucial for understanding market impact and liquidity demand.

```
Training Data - Trend Following:
Turnover (Dollars): 193600000.0
Turnover (Units): 5283991.976378969

Training Data - Momentum Trading:
Turnover (Dollars): 169000000.0
Turnover (Units): 4761653.766782999

Training Data - Mean Reverting:
Turnover (Dollars): 168000000.0
Turnover (Units): 4761894.704405507
```

```
Testing Data - Trend Following:
Turnover (Dollars): 80800000.0
Turnover (Units): 2197375.8470139145

Testing Data - Momentum Trading:
Turnover (Dollars): 17200000.0
Turnover (Units): 575571.3937364661

Testing Data - Mean Reverting:
Turnover (Dollars): 70200000.0
Turnover (Units): 1965221.9894255816
```

Fig 7 – Output of calculation of Turnover Dollars and Turnover Units for both train and test data.

The turnover values shown in the figure offer valuable insights into the performance and adaptability of three distinct trading strategies analysing both training and testing data, we observe notable fluctuations in turnover metrics across strategies, indicating varying degrees of responsiveness to changing market dynamics. Trend Following strategy exhibits a substantial decline in turnover when transitioning from training to testing data, Momentum Trading demonstrates an increase in turnover, particularly in units traded. Conversely, the Mean Reverting strategy experiences a significant reduction in turnover metrics during the testing phase.

The get the good understanding we have plotted moving average of turnover over 30 days

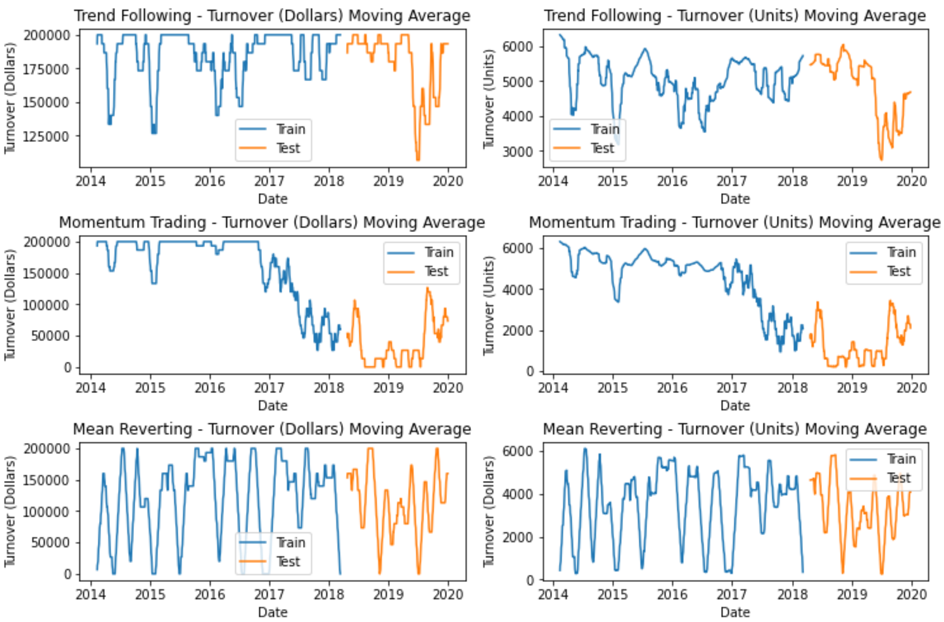

Fig 8 – Moving average of Turnover Dollars and Turnover Units plot for both train and test data.

In Trend following strategy plots, the strategy exhibits relatively stable turnover during the training phase, suggesting consistent performance. However, during testing, one of the plots display a significant deviation from the training phase, indicating a potential lack of generalization or adaptability to unseen data. The momentum trading strategy plots showcase a decreasing trend in turnover during the training period, with the testing phase initially aligning but later diverging. This suggests a shift in turnover patterns not accounted for during training, highlighting the importance of adaptability and robustness in trading strategies. The mean reverting strategy plots depict higher volatility in both the training and testing phases, with the testing data diverging significantly from the training trend.

There are periods where the moving average of turnover dollars and units is higher than certain periods. Specifically, these changes are more seen during the test periods, which may reflect market changes, shifts in strategy effectiveness, or a transition from a controlled training environment to a more variable testing environment.

The volatility of SPTL ETF and the moving averages of turnover in dollars and units may contain information on how the strategies perform. Generally, higher turnover periods happen in times of high market volatility when traders are continually readjusting their positions to respond to market fluctuations.

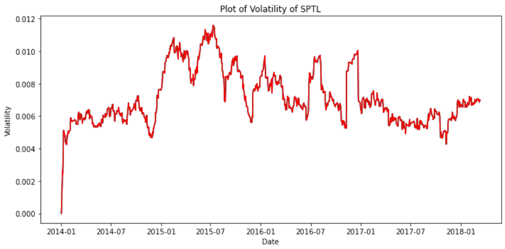

Fig 9 – Plot of Volatility of SPTL

By comparing the peaks in SPTL's volatility with the moving average of turnover, it becomes apparent that these spikes do not always coincide with spikes in turnover across the various trading strategies. In the Momentum Trading strategy, peaks in turnover dollars align closely with periods of high volatility, suggesting that this strategy may be sensitive to capitalizing on or being influenced by market volatility. However, for the Trend Following strategy, increased turnover during certain periods, such as 2017 and 2019, occurs independently of the highest volatility peaks in the SPTL plot. This observation hints that the strategy may identify opportunities irrespective of extreme volatility or could be responding to alternative market conditions. In nature, the relationship between turnover and SPTL's volatility is complex, indicating that different strategies exhibit varying sensitivities to market volatility and operate under distinct mechanisms.

The total PnL series was implemented for deeper analysis by an approach where any money that is not used is invested in the money market which attracts a risk-free rate. The total value of the trading account (ΔVt_{total}) changes over time as a function of both the trading PnL (ΔV_t) and the growth of the money-market capital account (ΔVt_{cap}).

$$\begin{aligned} V_{t+1}^{total} - V_t^{total} &= \Delta V_t^{total} \\ &= \Delta V_t + \Delta V_t^{cap} \\ &= \left(\frac{\Delta p_t}{p_t} - r_t^f\right)\theta_t \; + \; (V_t^{total} - M_t) r_t^f \end{aligned}$$

Formula taken form provide coursework

The change in total value from time t to $t+1$ (ΔVt_{total}) is calculated as the sum of the change in trading (ΔV_t) and the change in the growth of the money-market capital account (ΔVt_{cap}). The change in trading PnL is determined by the difference between the asset price change (Δp_t) divided by the asset price (p_t) and the risk-free rate (rf), multiplied by the trading position (θ_t). Meanwhile, the change in the growth of the money-market capital account is computed as the product of the difference between the total value of the trading account and the total margin used (Vt_{total} - M_t) where M_t is $|\theta_t|/L$ multiplied by the risk-free rate. By employing such a structure, we can capture the total PnL series over time, which not only includes the gains from trading but also the interest from the money-market investment, thus providing a clear picture of the strategy's performance.

By using above formula $\Delta V_{t,}$, ΔVt_{total}, and ΔVt_{cap} was calculated and their accumulated values were plotted.

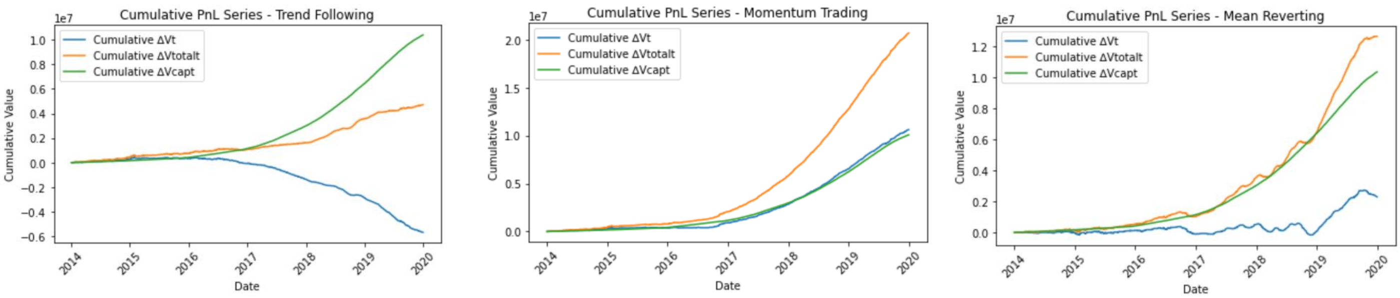

Fig 10 – Plot of Cumulative PnL series for all the strategies

The cumulative PnL chart, under the trend following strategy, exhibits a continuous decline of cumulative ΔV_t with an obvious rise in cumulative ΔVt_{cap} towards the end of the considered period, which indicates the change of the effectiveness of the strategy or the condition of the market. However, the momentum trading strategy gradually accumulates cumulative ΔV_t and ΔVt_{cap} with a main spike in ΔVt_{total} accumulated around 2018, implying a rather steady time period probably influenced by advantageous market trends or strategic shifts. On the other hand, the mean-reverting strategy exhibits a sturdy growth of cumulative ΔV_t and ΔVt_{total}, with a major surge of cumulative ΔVt_{cap} that is noticeable from late 2017 through early 2018, which is an indicator of profitability, or effectiveness that is probably caused by market dynamics and strategical improvement. Such developments afford access to valuable information regarding the efficiency of the strategies over time with periods of strength and possible places for improvement being brought into the picture.

The costs of funding denoted by r_f are a crucial factor in what we call the ‘excess return’ of leveraged systems. Rising funding costs would imply a drop in excess returns being in proportion with the increased expense of capital to stick with leveraged positions. An increase in funding costs amounting to 150% would surely affect the strategy negatively and the extra yield would instantly get removed and hence definitely make the strategy purely a losing one. The given plot is explaining the relation between Excess return and Excess return with 150% funding costs would even show you how much it affects. The plot that shows higher funding cost has undergone a bigger drop in excess returns which suggests that the effectiveness of the strategy is to a huge degree dependent on changes in funding costs.

Fig 11 – Plot of comparison between original excess return and excess return with 150% more cost funding.

As the position size is amplified using V_0 so margin effect is much stronger because of the built-in leverage in the position size. Therefore, any increase in r_f would immediately increase reliance on excess returns, making it possible for a good strategy to become unprofitable if the funding costs rise very much higher than the return on investments.

Results

For a proper evaluation of trading strategies, there is a need to consider reliable metrics and provide comprehensive information on both the returns and risks. To be more focused we have used the Sharpe Ratio (SR), Sortino Ratio, Maximum Drawdown, and Calmar Ratio as the main performance indicators. Such metrics help us set key performance indicators whose goal is to measure performance on a risk-adjusted basis and to determine the downside risk of our strategies.

The Sharpe Ratio, which is the critical indicator, expresses the excess return on a unit basis over the standard deviation of risk. As per [5] Sharpe ratios that are higher and correspond with superior performance are indicated by steeper slopes.

SR = (Mean Return−Risk-Free Rate)/Standard Deviation of Returns.

Its relative, the Sortino Ratio, filters this out, focusing only on the downside volatility, therefore, providing more in-depth information about the risk-adjusted returns. As per [5] Portfolio managers are rewarded to protect against returns below the minimum target by penalizing downside variability instead of total risk.

SortinoRatio = (Mean Return−Risk-Free Rate) / Downside Standard Deviation of Returns

In addition, the Maximum Drawdown stands for the maximum loss in percentage from the top to the bottom when looking at the worst-case scenario.

Similarly, the Calmar Ratio establishes connectivity between the annualized return and the maximum drawdown, thus imparting insights into the risk-adjusted performance over time.

Calmar Ratio = Annualized Return / Maximum Drawdown

Following the good practices, we have been hardworking enough to apply these metrics to training and test data sets. Through this complete assessment, the strategy performance can be carefully analysed under different market situations which can result in a better decision-making process in asset allocation and strategy optimization.

```
Metrics for Trend strategy:
Training Set:
Sharpe Ratio: -0.15
Sortino Ratio: -0.22
Maximum Drawdown: 206671704.44%
Calmar Ratio: -0.19

Test Set:
Sharpe Ratio: -0.93
Sortino Ratio: -1.09
Maximum Drawdown: 405569617.84%
Calmar Ratio: -0.56
```

```
Metrics for Momentum strategy:
Training Set:
Sharpe Ratio: 0.30
Sortino Ratio: 0.54
Maximum Drawdown: 10316912.04%
Calmar Ratio: 8.15

Test Set:
Sharpe Ratio: 1.23
Sortino Ratio: 2.66
Maximum Drawdown: 2750517.86%
Calmar Ratio: 144.96
```

```
Metrics for Mean_reverting strategy:
Training Set:
Sharpe Ratio: 0.01
Sortino Ratio: 0.01
Maximum Drawdown: 50019941.97%
Calmar Ratio: 0.03

Test Set:
Sharpe Ratio: 0.31
Sortino Ratio: 0.48
Maximum Drawdown: 75497164.86%
Calmar Ratio: 1.65
```

Fig 12 - Output of the calculation of performance metrics.

The figures of Trend, Momentum, and Mean-reverting strategies shown above present different performance results from the training period and the testing set significantly, the Trend strategy is rated as having a negative Sharpe Ratio in both sets, implying that there are risk-adjusted returns. The Sortino Ratio is also negative, which is indicative that the downside risk outweighs the possible downside gain. Furthermore, the extremely accumulate and Losses Ratio was noticed in both the train and test sets which raised the concern about the achieved returns in both. Unlike this, the Momentum strategy also shows positive values of Sharpe and Sortino Ratio in both sets indicating the desired risk-adjusted returns. Moreover, it had a low downside risk. The statistical indicators of the low Maximum Drawdown and high Calmar Ratio imply the strong and resilient nature of the asset's performance. So, the mean-reversing strategy performs moderately, it gains some ground towards the training set only in the nearest future in terms of Sharpe and Sortino ratios in the testing set. But in the landscape, its Maximum Drawdown is still high which is interpreted as big losses for the returns that are naturally less than average. That is to say, the Momentum strategy is among other things strongly consistent and stands the test of time, whereas the Trend and Mean-reverting strategies show serious weaknesses thus the need to keep on working on and improving them in a bid to make them even more effective.

The Rolling Sharp Ratio for the Strategies was plotted for better understanding

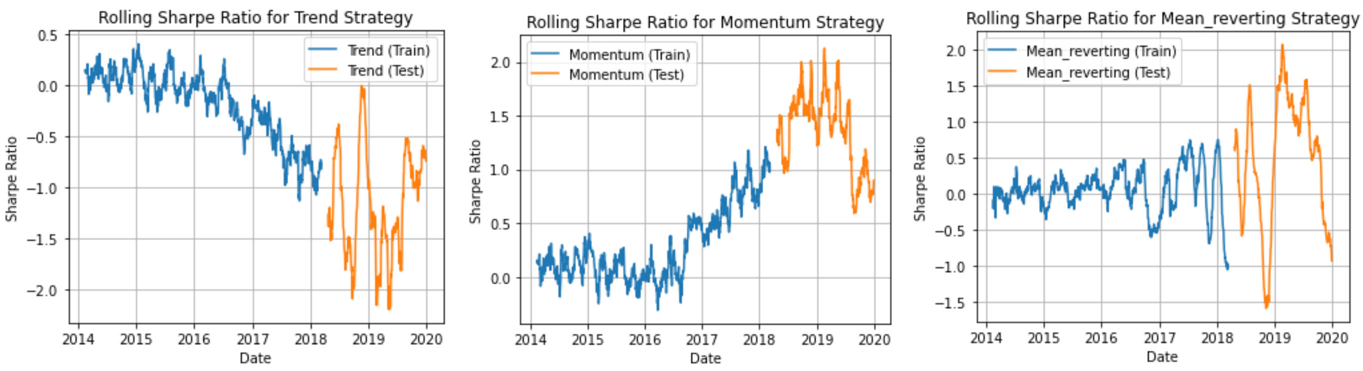

Fig 13 – Plot of Rolling Sharp Ratio for all the strategies for both train and test dataset.

The rolling Sharpe Ratio (SR) charts provide a visual overview of the divergence between the training data and test data in terms of performance for the three strategies. In the three methods, rolling Sharp Ratio is often higher during the training period rather than the testing period, implying a possible overfitting procedure where strategies learn patterns or noise that may not work generally for out-of-sample data. For instance, the Trend strategy is characterized by stable but low SR values during training periods and more volatile, mostly lower rolling Sharp Ratio values during test periods. The Momentum model does exhibit good rolling Sharp Ratio numbers in the training stage, and later, their values seem to be lower in the test phase. On the contrary, the mean-reverting strategy records high rolling Sharp Ratio variability in both periods but the most notable decrease comes during the test stage. This gap, however, implies the difficulty of strategies over-fitting to historical statistics, highlighting that future results should not be solely based on the past performance of financial modelling.

To boost consistency in the Sharpe Ratio (SR) across both the training and the testing sets, we can approach this issue with several strategies. Firstly, performing the robustness tests including the exploration of the strategy under different financial markets will provide insurance that it is not simply cropping up from the occurrence of temporal inconsistencies. Besides, justifying the strategies with sound economic or financial reasons other than numerical relations to historical data is also extremely important. Regular rebalancing strategies to accommodate changing market conditions can be employed, ensemble methods for diversification can be used, and techniques such as dynamic exposure modulation and drawdown controls can be implemented that can be used to lower risks and improve strategy performance consistency.

Discussion

The graph of Drawdown over time, and alongside historical rolling volatility 90-day, depicts the dynamics that are significant to the performance and risk of each strategy. We can measure to what extent a strategy is resilient during market jumps and financial volatility, as well as how the strategy performs overall.

$$DD_t = \max_{s \leq t}[PnL_s] - PnL_t$$

Formula taken form provide coursework

Where -

DD_t is the drawdown at time t.

$\max\{PnL_s\}$ represents the maximum profit and loss (PnL) value reached over the time period up to and including time t.

PnL_t is the profit and loss value at time t.

s is a variable representing a previous time, and the expression $s \leq t$ means the maximum PnL is considered over all times from the beginning of the period up to time t.

This formula was used to plot the Drawdown charts over time

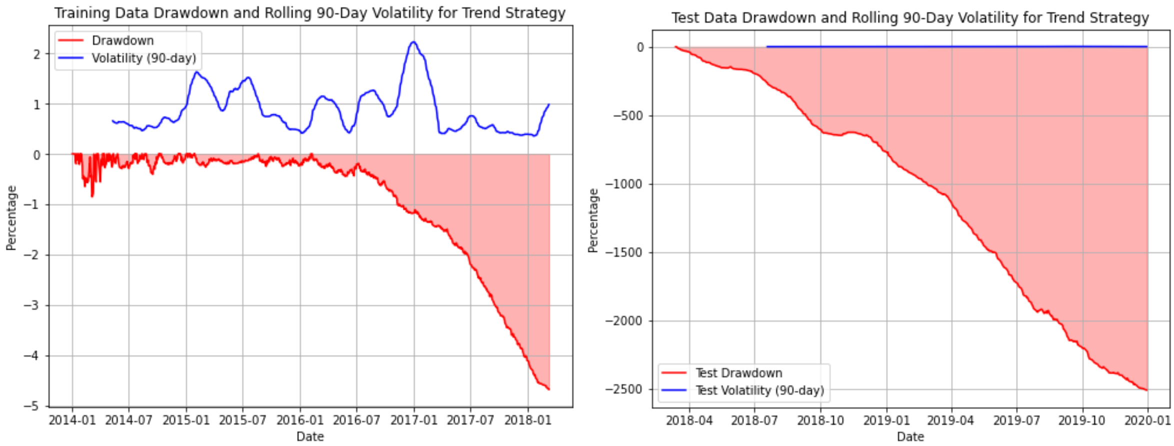

Fig 14 – Drawdown chart for Trend following strategy for both train and test data.

The chart for the Trend strategy's Drawdown and volatility risk which was provided for both the training and the test data is a stunning visual picture of the strategy's risk profile over time. The graph shows that the drawdown in the training set declines, pointing to a continuous drawdown for which the loss started from a high point to a low point. The biggest negative drawdowns usually happen at the same time as when the rolling 90-day volatility reaches its peak, indicating that periods of particularly high market volatility are seminally correlated to the scope of potential losses. Such a link is only logical, trend strategies tend to be based on persisting market moves and enhanced volatility. In the test set, however, the scope of the drawdown becomes larger, the curve sloping more steeply. It has become clear that the drawdowns of the model during the test trial are deeper and more protracted, which, in turn, leads to the assumption that it may not have been optimized for the market situation of the test period, as it was for the training period. The volatility trend in this area appears to move toward higher values, speaking to the potential correlation between higher volatility and more severe drawdowns.

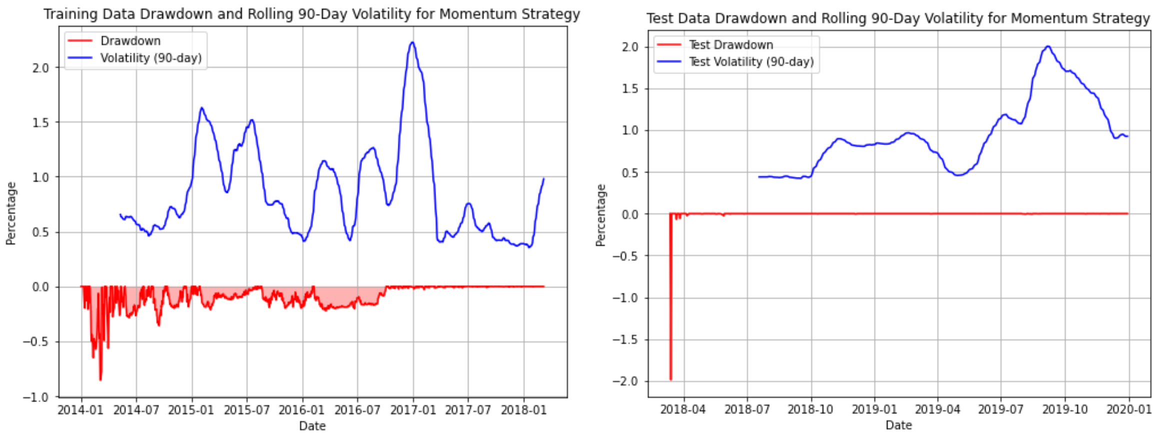

Fig 15 - Drawdown chart for Momentum strategy for both train and test data.

The Momentum strategy chart of drawdown and volatility contrasts with the Trend strategy. During the training period, Momentum strategy drawdowns are more concentrated, which suggests a narrower and shorter-term period of loss. Interestingly, the drawdowns do not seem to be directly correlated with the rolling 90-day volatility, while it gives evidence that the strategy did manage to capture and move with the markets by catching up and going with the trending movements. But, in the test set, drawdowns tend to be more severe and it might be due to a deficiency in out-of-sample performance or inability to adjust to the changing market conditions. Still, volatility spikes do not always correspond with the deepest drawdowns, which indicates the possibility of difficulties in identifying the end of the trend and adaptation to market dynamics.

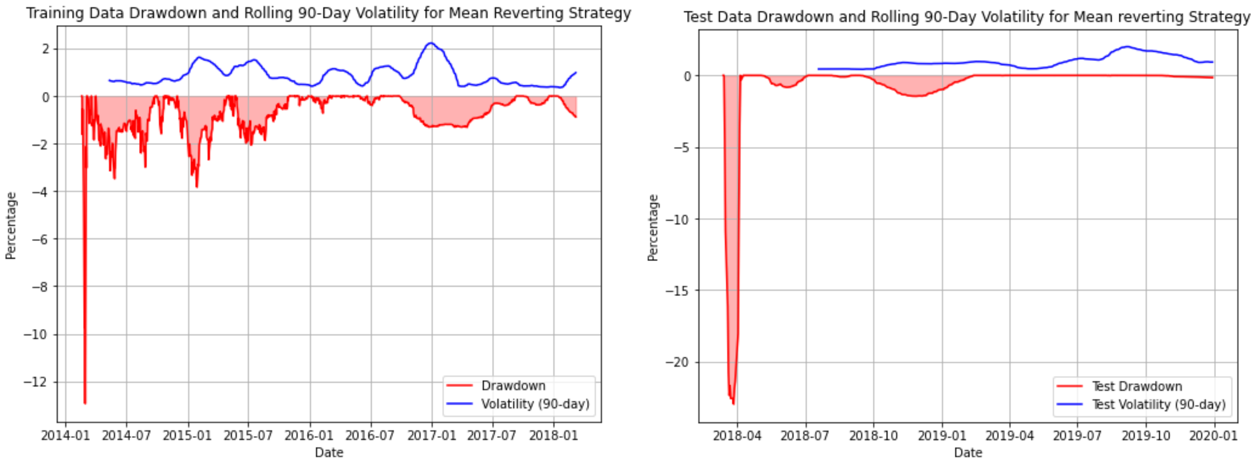

Fig 16 - Drawdown chart for Mean reverting strategy for both train and test data.

A more stable way of managing risk would involve using the margin differently using chart drawdown results for all cases to measure underlying volatility for the Trend, Momentum, and Mean Reverting strategies. In the trend strategy, there were times that drawdown increased when volatility was high, so, you should use a safer approach of reducing the margin to avoid losses during such periods. In contrast, during times with low volatility, margin increases can take advantage of the slow variations. As the correlation between volatility and drawdowns in the Momentum Strategy is less correlated, probably this strategy has some mechanism in its trend-following ability already. Reducing margin during volatility spikes could still be highly beneficial. The Mean Reverting Strategy went through major drawdowns during high volatility, excessive margin usage during these periods may increase a strategy's sensitivity to large negative price fluctuations. Implementation of such dynamic risk management methods will include live tracking and integration of volatility forecasts, as well as the adoption of strict risk control techniques such as stop-loss orders to optimize margin use across all trading strategies.

The analysis of the drawdown charts shows that we can use safer margins based on underlying asset. The analysis shows that there is a clear relationship between market volatility and drawdowns, or periods of loss, for various trading strategies, such as trend, momentum, and mean reversion. For example, drawdowns typically increase during periods of high volatility, suggesting increased risk. As a result, carrying out a task with a strategy that lowers margin usage during these irregular times can help to minimize possible losses and improve risk management overall. This technique significantly increases the use of margin across a range of trading strategies by ensuring a more dynamic and adaptive response to market conditions. Trading experts can effectively adjust their margin usage to current market conditions by implementing volatility forecasts and using risk control strategies like stop-loss orders. This improves the safety and reliability of their trading strategies.

Conclusion

Ultimately, this research analyses algorithmic trading strategies for making money with SPTL funds—which track Treasury bonds with a long duration. We have looked at how well various trading strategies work to maximize profits while effectively managing risks by analysing historical data from 2014 to 2019. Our analysis has made clear ideas like daily profit, turnover, and drawdown and provided insights into risk management techniques and ways to improve returns. We have explored the effectiveness of these strategies and their implications in the context of market fluctuations, particularly in response to interest rate changes, by using simple and direct performance metrics such as Sharpe Ratios. The approach of increasing positions with initial capital ensures that the profit and loss remain within the prescribed limits of the book size, contributing to effective risk management. Through a critical analysis of the different strategies and techniques, this report gives investors the information necessary to manage leveraged ETFs like SPTL with understanding, opening in an ever door to better investment choices and higher returns world of algorithmic trading.

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