S&P500 ETF Trading using Traditional and Advanced Strategies

Abstract

This study focuses on building 3 trading strategies for the S&P500 ETF during the period 2014-19. Through this research, we aim to serve two important agendas. One, is figuring out the best trading strategy for our exchange-traded fund (ETF). Second, learning about characteristics of the fund (our dataset) by experimenting with various factors and variables that influence the result of our trading strategies. For these purposes, we employed traditional Mean Reversion and Crossover Strategy and advanced Neural Network (MLP) Regressor model. We found the most impressive performance from one traditional mean reversion strategy and one neural network (MLP) Regressor which are built using interesting brute-force and test-train-split approach, respectively. We also explore the possibility of combining these traditional and advanced models, which produce astounding performance for our S&P500 ETF trading.

Introduction

S&P500 ETF or better known as SPDR (Standard & Poor's depository receipt) is the first ETF listed in the U.S. in January 1993, when introduced by State Street Global Advisors, which tracks the S&P 500 Index. We select the time period from 1 January 2014 to 31 December 2019 for our strategies. This is considered to be a very bullish period for the index as the price consistently rose from \$180 to \$320 during this 6-year span. We assume r_t as the rate of return when we borrow a unit of SPDR at the end of trading period on day $t-1$ i.e., at Closing Price on day $t-1$ (p_{t-1}) and sell it at the end of trading period on day t i.e., at Closing Price on day t (p_t) . The SPDR returns performance over the years is visualised in Figure 1. The behaviour of the SPDR returns is as random as for any other stock and it has significant volatility as the daily returns vary from -4.5% to 4.5% over the period.

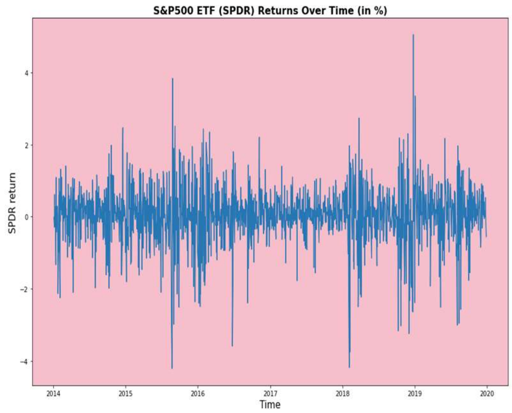
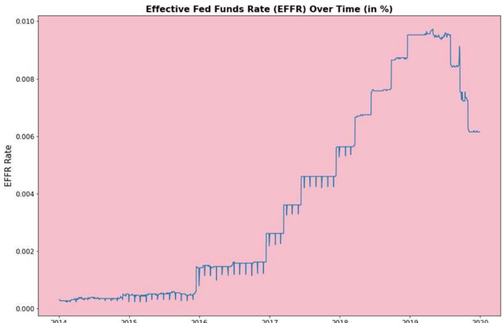


Figure 1: SPDR Daily Returns During the Period January 2014 - December 2019

EFFR (Effective Fed Funds Rate) is employed as a proxy for the risk-free rate, converted from annualised rate to daily rate r_t^f. Its missing values are filled using ffil (forward fill) which seems reasonable as the rate is generally expected to remain relatively stable over short periods of time. A unit of SPDR will cost p_t at time t, which we have to finance at the risk-free rate. This gives us the daily excess return per unit of SPDR, which can be mathematically expressed as:

$$r_t^e = \frac{p_t - p_{t-1}}{p_{t-1}} + r_t^f$$

The above equation is different from the one mentioned in the coursework outline as we use closing prices of 2 days rather than opening and closing price of the same day (as was assumed in the document). Prior to the calculation of the excess returns, the SPDR dataframe was merged with EFFR using left join, thus removing any missing values from the SPDR data along with the rest of the row. This, along with the use of ffill for EFFR rate, results in a cleaned and consistent dataset which is expected to give us accurate excess returns for each day in the period. The EFFR daily rate and the excess returns are visualised in Figures 2 and 3. The EFFR daily rate projections resonates with our understanding of it being relatively stable over short terms. Lastly, the excess returns seen in Figure 3 indicates narrow difference from the SPDR returns projections, due to consistent and less significant EFFR rate throughout the period.



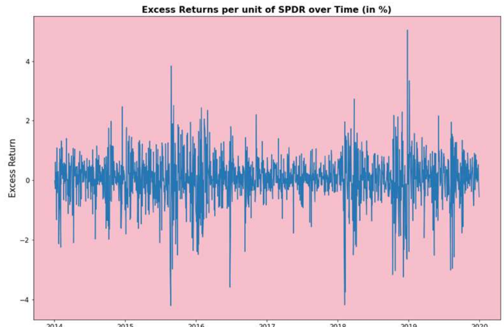


Figure 2 and 3: Effective Fed Funds Rate (EFFR) and Excess Returns per unit of SPDR over Time

Methodologies

Defining the process: It's crucial to discuss the ground rules we employed which would help in clarifying the process and choices made behind the trading strategies. First, for each trading strategy, we apply the 60/40 portfolio rule which means investing 60% of the capital in stocks and 40% in the bond & money market. A significant capital in bond market is crucial for diversification, but also is important as we are investing in a significantly volatile financial instrument. No stock investments are made within the first time-window period due to our calculation of moving averages being incomplete, leading to generate no proper trading signals until that first period of days has elapsed. So, the whole total of 200,000 is decided to be taken as unused capital, increased by the risk-free rate for the initial window period. Further, the total capital V_t^{total} is assumed to be total amount of money accumulated just as we close a position at the announcement of closing price on day t and trading capital V_t (which is unleveraged) and unused capital V_t^{cap} are the amounts invested after the announcement of closing price on day t, distributed in the 60/40 ratio of V_t^{total}.

The unleveraged trading capital V_t, times the leverage L, gives us the total trading capital that can be used to invest in stocks. So, the position of our strategy θ_t, taken after the announcement of the closing price on day t, can be given as:

$$\theta_t = V_t * L \text{ for a long position and } \theta_t = -V_t * L \text{ for a short position}$$

We decide to open each position for roughly a day, i.e. closing it as soon as the announcement of the closing price on day $t+1$ is released. This gives us the daily trading PnL ΔV_t as:

$$\Delta V_t = \quad r_t^e * \theta_t.$$

The unused capital V_t^{cap} and the daily cash growth ΔV_t^{cap} can be given as:

$$V_t^{cap} = V_t^{total} - \frac{|\theta_t|}{L} = V_t^{total} - \frac{V_t * L}{L} = V_t^{total} - V_t = V_t^{total} - 0.6 * V_t^{total} = 0.4 * V_t^{total}, \text{ and}$$

$$\Delta V_t^{cap} = V_t^{cap} * r_t^f$$

This results in daily total PnL ΔV_t^{total} as:

$$\Delta V_t^{total} = \Delta V_t^{cap} + \Delta V_t$$

And the total capital earned after closing the position right when the closing price on day t+1 is announced is:

$$V_{t+1}^{total} = V_t^{total} + \Delta V_t^{total}$$

This again would be divided as per 60/40 ratio for V_{t+1} and V_{t+1}^{cap} and this iterates over till n-1 for our trading process. additional quantity called residual capital which is the amount of money left after investing the trading capital for the whole number of stocks rather than decimals, which is only logical when dealing in the financial markets. This residual capital is then simply added to the unused capital of the same day on which the daily cash growth is then calculated.

For this research, we employ Neural Network model, Mean Reversion and Crossover Strategies. Neural Network model, particularly the MLP (Multilayer Perceptron) Regressor model, is used as a trading strategy by predicting the expected price using training and testing dataset. The signals are generated using the expected price and the current price, and hyperparameter tuning has been applied to improve the trading performance. For the Mean reversion and Crossoever strategies, we believe using a brute force approach, rather than the train-test split method, is the most optimal approach. A brute force approach allows us to directly simulate the results with all potential values, guiding in choosing the optimal value for the parameters of our trading strategies. For both aforementioned strategies, we put the parameters in the loop and select the two best parameter values, i.e., two best models within each trading strategy. The unique methods applied to the traditional and advanced strategies allows us to gain an in-depth understanding of the characteristics of the S&P500 ETF and each strategy, thus fulfilling both aforementioned agendas of our study.

Mean Reversion Strategy: A widely used trading strategy which is based on the assumption that the stock prices over time would revert to their long-term average levels. In essence, it involves buying an asset when its price is below its historical average and selling it when the price rises above the average.

In the case of the S&P500 ETF, a mean reversion strategy could be effective due to the historical characteristics of the ETF during the time period 1 Jan 2014 to 31 December 2019. During the time period in question, the S&P500 ETF experienced significant growth, driven by a strong U.S. economy and low interest rates. However, despite this growth, the S&P500 ETF also exhibited some periods of volatility and mean reversion during this time period. For example, in early 2016, the ETF experienced a sharp decline, followed by a period of sideways movement before resuming its upward trend. Additionally, in late 2018, the ETF experienced a significant decline, followed by a period of consolidation before resuming its upward trend again. Given these characteristics, a mean reversion strategy using a simple moving average (SMA) could be effective. Specifically, if the price of the ETF falls below the SMA, it could be seen as a signal to buy the ETF, as the price may be oversold and due for a rebound. Conversely, when the price rises above the SMA, it could be seen as a signal to sell the ETF, as the price may be overbought and due for a correction.

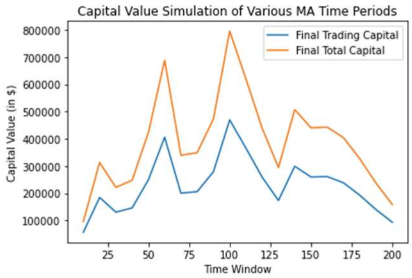


Figure 3: Simulation of Various MA Time Periods for Mean Reversion Strategy

Using brute force approach, we simulated the trading and total capital results over the 10 to 200 days MA range which can be seen in Figure 4. The 60-day MA and 100-day MA have had the highest final trading and total capital accumulated over the 6-year period. Thus, we decide to choose these two variations of the mean reversion strategies as our models. The various technical indicators and results obtained in the next section helped decide the best mean reversion strategy out of the two, while also understanding how different MA periods impacts the trading of S&P 500 ETF.

Crossover Strategy: A trading strategy that involves using multiple moving averages (MAs) to identify trends in asset prices. The basic idea behind this strategy is that when a short-term MA crosses above or below a long-term MA, it indicates a potential trend change in the asset price. In context of our financial instrument, when the short-term MA crosses above the long-term MA, it is considered a buy signal, while a crossover in the opposite direction is considered a sell signal. We selected this strategy because the 2014-19 period of the EFT saw it behaving as a very bullish stock due to its strong overall growth with occasional pullbacks and periods of heightened volatility during it.

The brute-force approach is applied for the short-term and long-term MA parameters, which was simulated using varying values of short-term and long-term MA along with varying gap between the MAs. This is done in order to mark the trading performance of the strategy in practically all possible values of the MAs, thus shortlisting the two variations that register much hope with the crossover strategy performance. With the context of $200,000 as initial capital applied in the crossover strategy, the two best variations of the parameters providing optimal trading performance are found to be 60 short-term and 130 long-term moving averages, and 70 short-term and 150 long-term moving averages.

Neural Network (MLP) Model: The MLP model is a type of artificial neural network that is commonly used for regression and classification tasks but can also be utilised for a trading strategy. It consists of an input layer, one or more hidden layers, and an output layer. Each layer contains a set of nodes or neurons, which are connected to the nodes in the adjacent layers. The model is trained by adjusting the weights and biases of these connections to minimize the error between the predicted output and the actual output.

In the context of our security, S&P500 ETF, it exhibited certain characteristics of mean reversion during the period 2014-19 as discussed in previous section. So, we use variations of the moving average (MA) values (particularly SMA-100) as signals for our training set, then employ the MLP model to predict the future price of the ETF based on these signals and make trading decisions accordingly. The opening, low, high and closing prices of the previous day are taken as independent variables to predict the closing price for the next day, which is our predictor variable. If the expected stock price for the next business day is more than the current stock price, we take a long position and when expected less than the current stock price, we take a short position. Hyperparameter tuning on hidden layer sizes, learning rate and maximum iterations has been performed using grid search with cross validation, that has significantly improved the efficiency of the signal detection for our MLP model.

Results and Discussions

We assessed the performance of the trading strategies using countless metrics, including various technical indicators like Sharpe Ratio, Maximum Drawdown, Drawdown Chart, etc. In each plot visualized (especially related to trading) is finding y-axis values 0 for some initial time period, which is due to our process of starting to invest only when we have the initial MA data required for the trading signals detection.

Position of the Strategies

For all strategies, we use the entire leveraged trading capital available as our long or short position. So, the positions across time in all strategies always lie either on the upper or lower bound, as exhibited by Figures 4, 5 and 6. Figures 4 and 5 depict the visualization of the position of the strategies for both mean reversion and crossover strategies. For the mean reversion strategies, the position value across the first 3 years impressively grows more than two and four times for the SMA-60 and SMA-100 strategies, respectively. While SMA-60 strategy maintains its position well by dynamically changing signals from 2017 to 2018, the SMA-100 takes the short position pretty much for the year, which is contradictory as the price of SPDR increases from $220 to $260 during that period. The position of both crossover strategies does not have dynamic change of signals, which is also consistent with our expectation as SPDR had a bullish period during that time with less fluctuations. However, the positions of the strategies have almost remained under 1 million which is less than half of what was achieved by mean reversion strategy, suggesting a scope of improvement for the crossover strategies. The time axis in Figure 6 does not follow the general 2014-19 scale, as the data has been split for training and testing dataset. However, important observation that can be made for training set is its impressive gain in capital in the first-half and almost equivalent dip thereafter, thus overall performance is unsatisfactory. Further, the value of the position for the test set has been gradually increasing over time. The final position has almost been doubled, which is also in a span of less than 2 years.

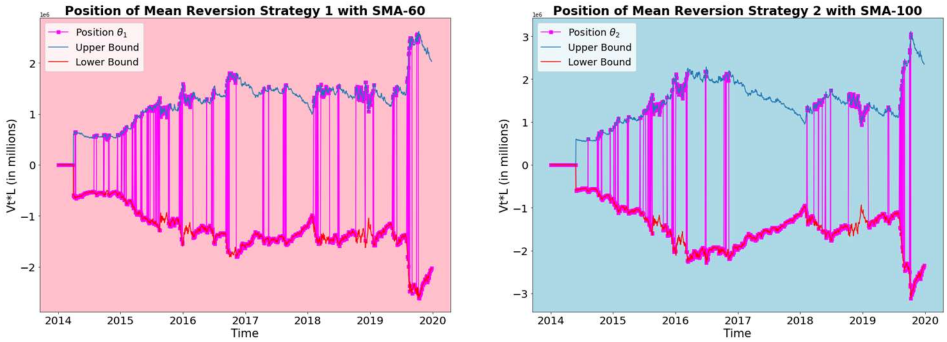


Figure 4: Position of the Mean Reversion Strategies with SMA-60 and SMA-100

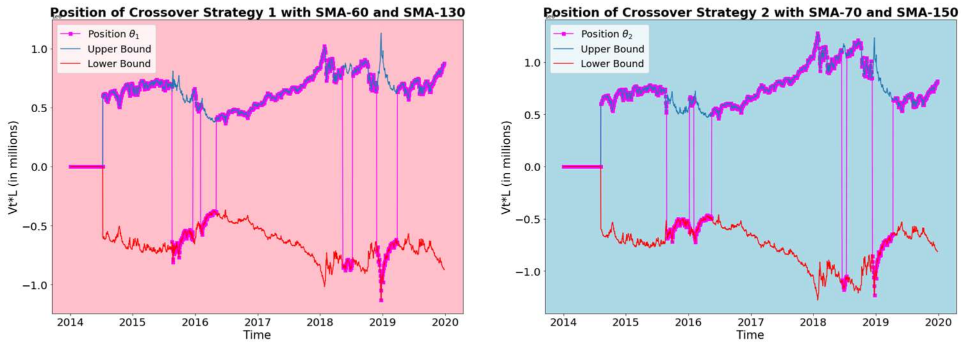


Figure 5: Position of the Crossover Strategies with SMA-60, SMA-130 and SMA-70, SMA-150

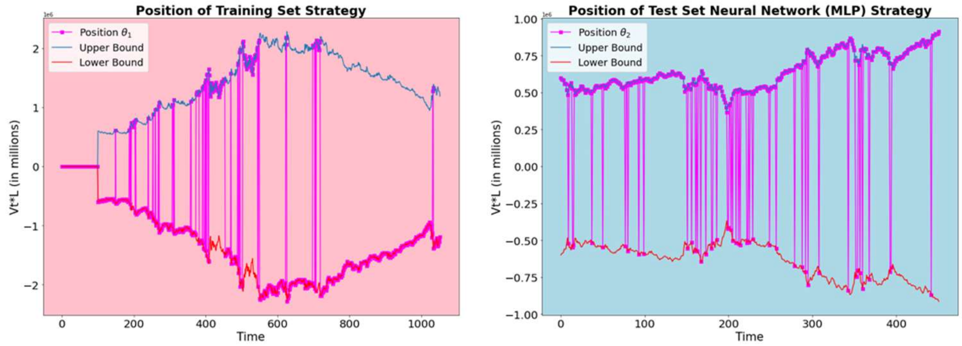


Figure 6: Position of the Training and Testing Set of the Neural Network (MLP) Regressor Strategy

Turnover Dollars and Turnover Units

$$\text{Turnover Dollars over Time} = \Sigma_1^T |\Delta\theta_t|$$
$$\text{Turnover Units over Time} = \Sigma_1^T \left|\frac{\theta_{t+1}}{p_{t+1}} - \frac{\theta_t}{p_t}\right|$$

For the mean reversion strategies, the turnover in units and dollars traded over time are 1451099 and \$340.49 million for the SMA-60 strategy and 1270257 and \$292.05 million for the SMA-100 strategy. For the crossover strategies, the turnover in units and dollars traded over time are 102906 and \$26.60 million for the SMA-60 and SMA-130 strategy and 115125.0 and \$30.34 million for the SMA-70 an SMA-150 strategy. But the training and testing set of our Neural Network model register a higher turnover dollars and units over time which are 862891 and 176.80 million, and 349128 and \$98.08 million, respectively. Overall, it can be said that testing set of Neural Network had an impressive performance as even with significantly fewer turnover units than the training set, it produced a great turnover in dollars trading the S&P500 ETF.

Trading PnL, Cash Growth and Total PnL performance

The mean reversion strategies have a initial randomly close-to-equivalent positive and negative daily trading PnL as seen in Figure 7. The daily trading PnL significantly increases in magnitude near to the end of the plot. The cumulative trading PnL in Figure 10 also reflects that as we see a sharp increase in the final year, which means the strategy benefitted from the opportunity of high volatility in SPDR prices, from \$240 to \$320, during that time. Daily and cumulative cash growths of these strategies depicted in Figure 12 and 14 shows a steady yet fluctuating increase in cash growth which leads to an exponential cumulative curve. However, its magnitude is not significant as compared to daily trading PnL. So, we have a total PnL performance mostly determined by trading, leading to almost mirror projections of the trading PnL curves with the total PnL performance (daily and cumulative) in Figure 16 and 19. However, the crossover strategies haven't been as efficient as mean reversion strategies in trading the S&P500 ETF. We have much high negative daily trading PnL especially at the start of 2019 as seen in Figure 8. This could be because the SPDR prices took a steep dive at the end of 2018, which the strategy could have failed to predict. This is also evident with cumulative trading PnL graph shown in Figure 10 where we see the amount plummeting to nearly 0 during that time. The strategy eventually recovered a bit at the end of 2019 as SPDR behaved overall bullish during that time. This similarly impacted its daily and cumulative cash growth seen in Figure 12 and 14, and had an identical total PnL performance shown in Figure 17 and 19, again due to low magnitude of cash growth. With the training set where we implemented mean reversion strategy with SMA-100 for Neural Network model, we see very similar performances to Mean Reversion Strategy 2, as should be the case. However, unique trading PnL behaviour has been observed for the test set Neural Network strategy in Figure 9. The curve seems to have a small oscillating behaviour around y=0 line, which indicates that the strategy fluctuates and changes signals very frequently, leading to high turnover in units as seen earlier. This is also evidenced by its cumulative trading PnL in Figure 11 depicting randomness with an overall outcome that the strategy recovers its investment in the second half of its term. Similar behaviour is found with the daily cash growth and cumulative total PnL graphs in Figure 13 and 20, respectively.

a) Daily Trading PnL Diagrams

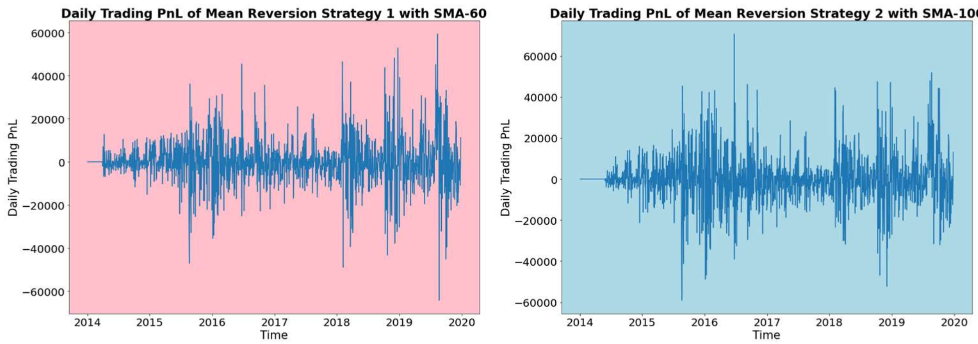


Figure 7: Daily Trading PnL of Mean Reversion Strategies with SMA-60 and SMA-100

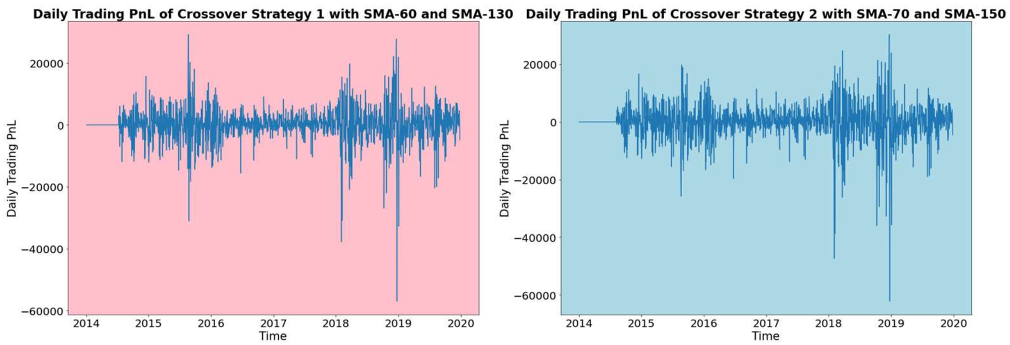


Figure 8: Daily Trading PnL of Crossover Strategies with SMA-60, SMA-130 and SMA-70, SMA-150

Figure 9: Daily Trading PnL of Training and Testing Set of the Neural Network (MLP) Regressor Strategy

b) Cumulative Trading PnL Diagrams

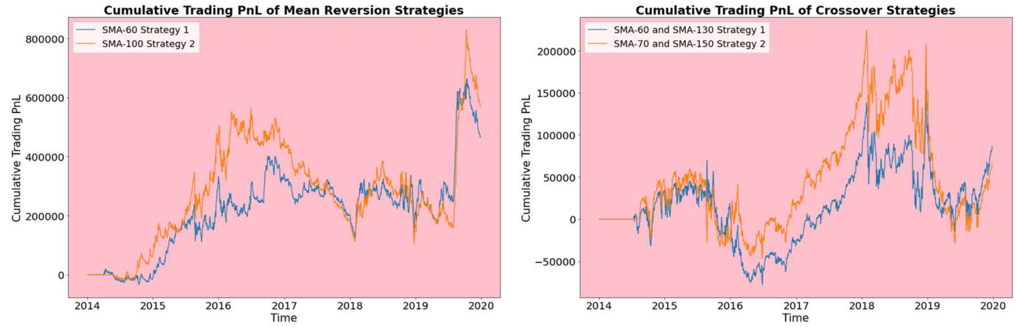


Figure 10: Cumulative Trading PnL of Mean Reversion and Crossover Strategies

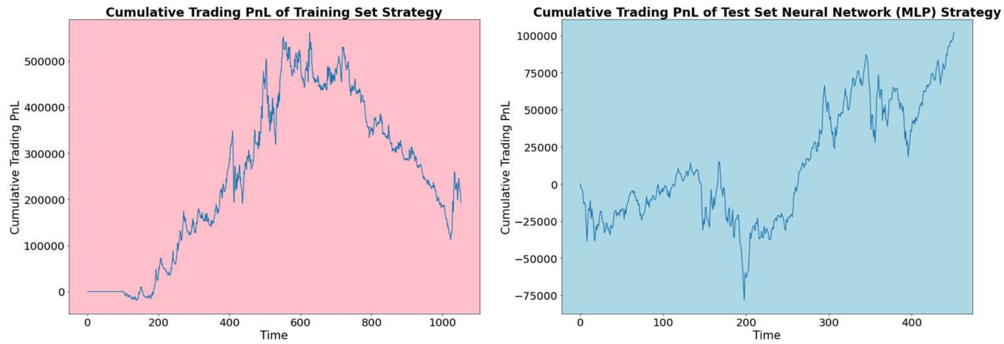


Figure 11: Cumulative Trading PnL of Training and Testing Set of the Neural Network (MLP) Regressor Strategy

c) Daily Cash Growth Diagrams

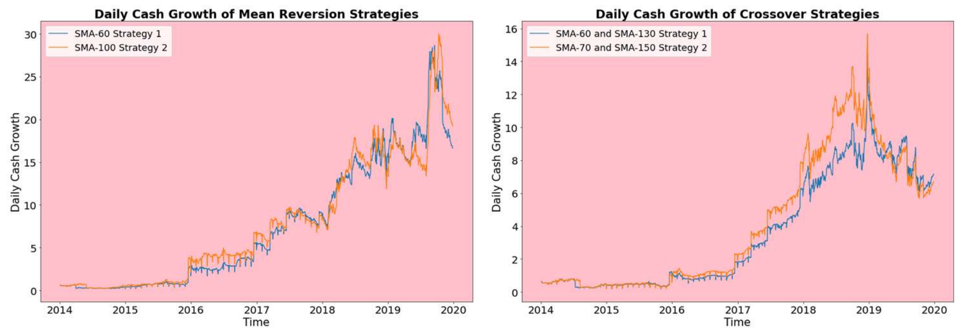


Figure 12: Daily Cash Growth of Mean Reversion and Crossover Strategies

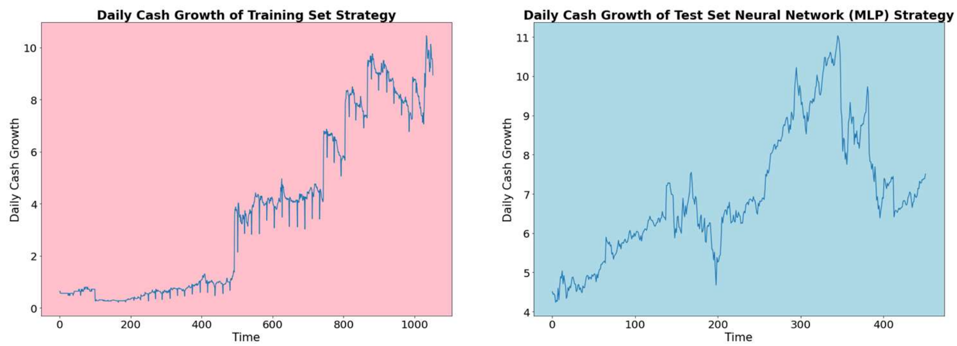


Figure 13: Daily Cash Growth of Training and Testing Set of the Neural Network (MLP) Regressor Strategy

d) Cumulative Cash Growth Diagrams

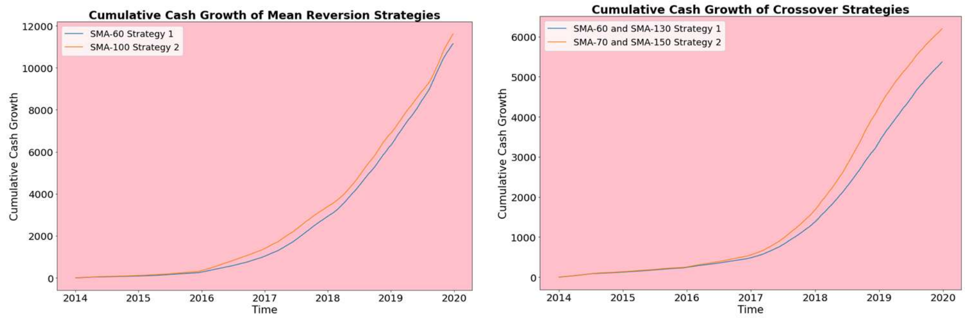


Figure 14: Cumulative Cash Growth of Mean Reversion and Crossover Strategies

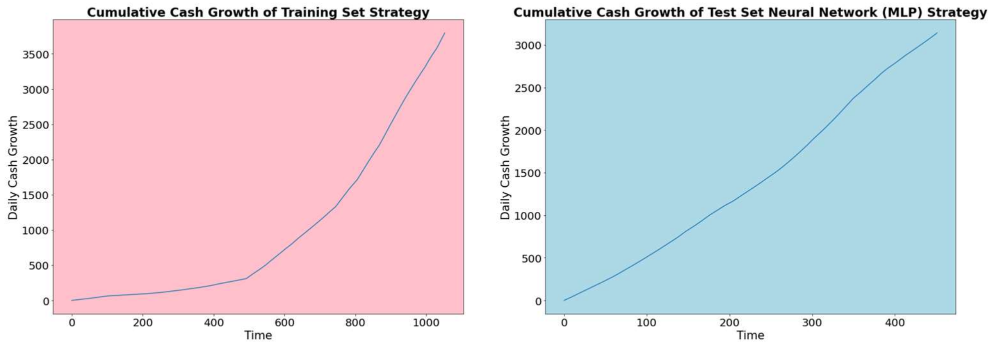


Figure 15: Cumulative Cash Growth of Training and Testing Set of the Neural Network (MLP) Regressor Strategy

e) Daily Total PnL Diagrams

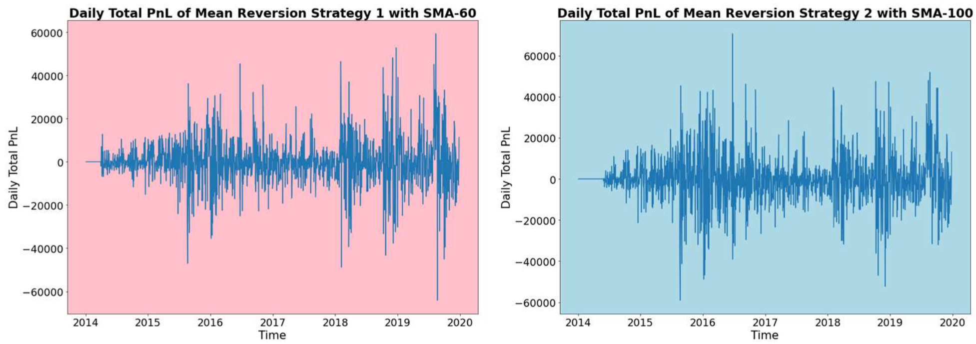


Figure 16: Daily Total PnL of Mean Reversion Strategies with SMA-60 and SMA-100

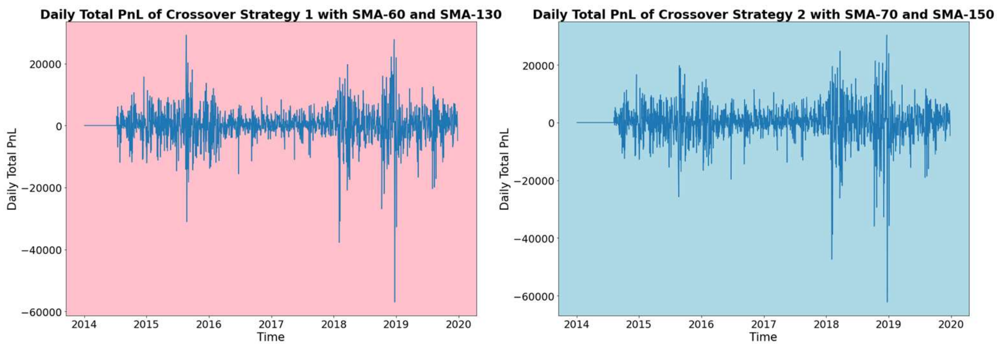


Figure 17: Daily Total PnL of Crossover Strategies with SMA-60, SMA-130 and SMA-70, SMA-150

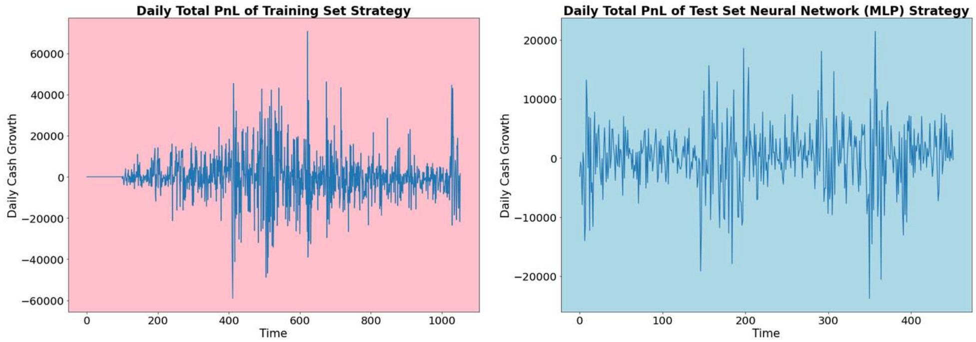


Figure 18: Daily Total PnL of Training and Testing Set of the Neural Network (MLP) Regressor Strategy

f) Cumulative Total PnL Diagrams

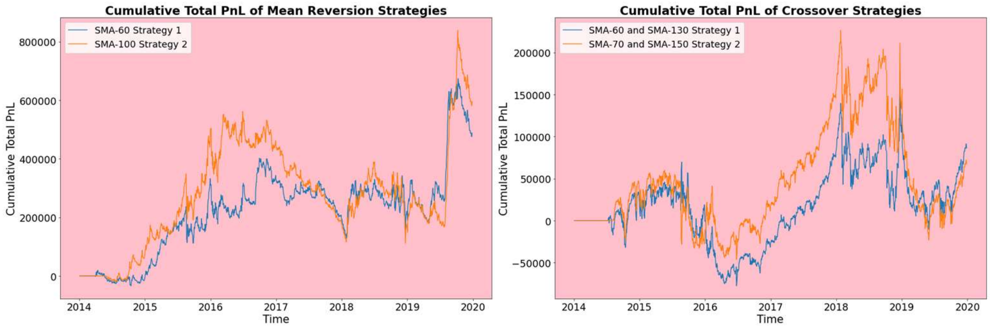


Figure 19: Cumulative Total PnL of Mean Reversion and Crossover Strategies

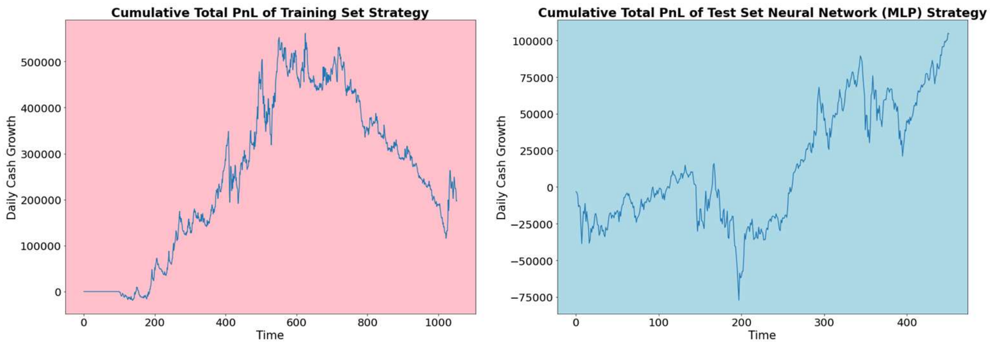


Figure 20: Cumulative Total PnL of Training and Testing Set of the Neural Network (MLP) Regressor Strategy

Sharpe Ratio (SR) is a measure of risk-adjusted performance that takes into account both the return and the volatility of an investment. It is expressed as:

$$\text{Sharpe Ratio (SR)} = \frac{\mu}{\sigma}$$

where μ and σ represent the mean and std. deviation of the excess returns of our trading strategies. Daily Sharpe Ratios are annualized by multiplying by $\sqrt{252}$. For the mean reversion strategies with SMA-60 and SMA-100, we have 0.48 and 0.53 as Sharpe ratios, respectively. Thus, SMA-100 strategy has a better risk-adjusted performance. Furthermore, the Sharpe ratio for Crossover Strategy 1 and 2 are 0.16 and 0.11, respectively which is underwhelming. Interestingly, the Sharpe Ratios for the training and testing set of our Neural Network model are 0.27 and 0.65. Thus, it's likely that the test neural network strategy has the best risk-adjusted performance.

Sortino Ratio is also a measure of risk-adjusted performance, but it focuses only on downside risk. It is expressed as:

$$\text{Sortino Ratio} = \frac{\mu}{\sigma^{neg}}$$

where σ^{neg} is the std. deviation of only the negative excess returns of our trading strategies. Mean Reversion Strategy 1 and 2 have Sortino ratio equal to 0.65 and 0.75 and for Crossover Strategy 1 and 2 are 0.18 and 0.12. For the Neural Network model, we get 0.37 and 0.87 for our training and testing set strategy. The fact that the Sortino Ratio is generally higher than the Sharpe Ratio for our strategies suggests that the trading strategy is generating positive returns while also managing downside risk better than the Sharpe Ratio suggests. Again, the test neural network strategy is found to have most optimal risk-adjusted performance with 0.87 Sortino Ratio.

Maximum Drawdown (MMD): A measure of the largest loss from a peak to a trough experienced by a trading strategy. It can be expressed in our notation as:

$$MDD = \frac{\min(cum\ \Delta V_t) - \max(cum\ \Delta V_t)}{\max(cum\ \Delta V_t)}$$

A lower maximum drawdown indicates that the strategy experienced smaller losses during its worst period, indicating better risk management. Based on the maximum drawdown results, the Mean Reversion strategies have the lowest maximum drawdown (-1.05 and -1.02), followed by the Neural Network models (-1.03 and -1.77), and then the Crossover strategies (-1.44 and -1.20). Overall, there is a large scope of improvement with each strategy as all can lose more than 100% of their gains.

Calmar Ratio is a measure of risk-adjusted performance that assesses the return of an investment relative to its maximum drawdown over a given period. We decide to take ARR (Annual Rate of Return) by converting our daily trading PnL (the steps mentioned in the Jupyter notebook), and the formula can be expressed as:

$$Calmar\ Ratio\ = \frac{ARR}{MMD}$$

Based on the results obtained, the Mean Reversion Strategy with SMA-100 has a better risk-adjusted performance compared to the Mean Reversion Strategy with SMA-60, as the Calmar Ratio for SMA-100 is higher at 0.68 compared to 0.54 for SMA-60. The Calmar Ratios for the Crossover Strategies are very low, at 0.057 and 0.015, indicating that these strategies have not performed well in terms of risk-adjusted returns. Interestingly, the Calmar Ratios for the Neural Network Models are also relatively low, at 0.25 and 0.18 for the training and testing sets respectively. This suggests that while the Neural Network models may have performed well in terms of Sharpe Ratio and Sortino Ratio, they have not been able to generate high returns in relation to their maximum drawdown.

Drawdown Chart with rolling 90-day SPDR volatility

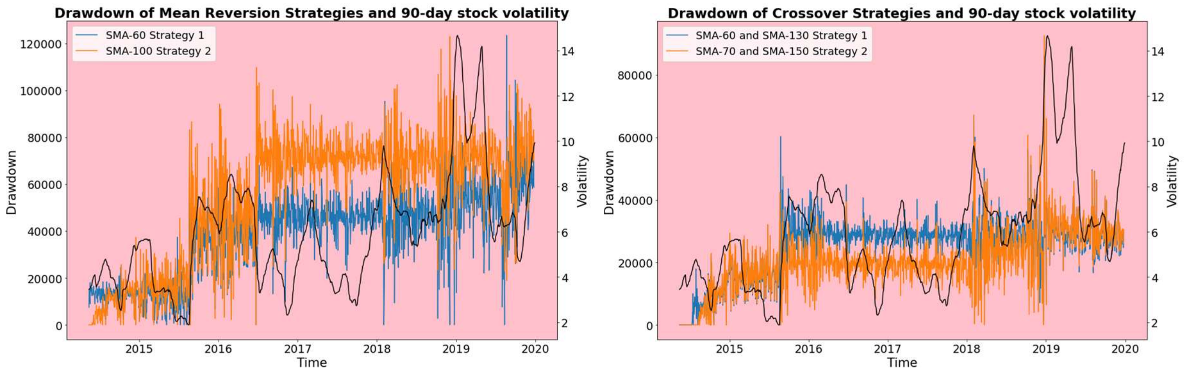


Figure 21: Drawdown Chart with rolling 90-day SPDR volatility for Mean Reversion and Crossover Strategies

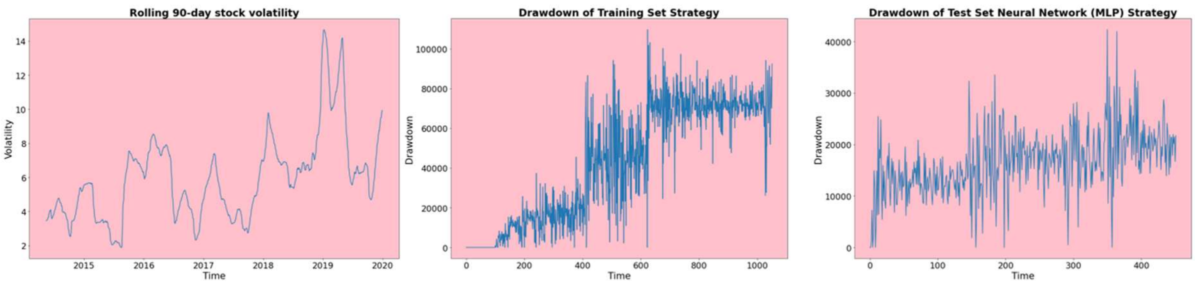


Figure 22: Drawdown Chart with rolling 90-day SPDR volatility for Training and Testing Neural Network Strategies

For the mean reversion and crossover strategies, the biggest drawdown was seen in the second half of 2018. This can also be said for the test set Neural Network strategy which represents trading in the last two years (2018 and 2019), where we can see drawdown doubled from 20000 to 40000 during the same time. The reason for this, which also emphasized when during the discussion of the Trading PnL, Cash Growth and Total PnL performance, is that the SPDR price time series saw the biggest 6-year dip from \$280 to \$240 in a span of less than 6 months. This can also be studied from the 90-day volatility measure alongside the drawdowns in Figure 21 and 22 where we see a significantly high volatility during that time. Another significant drawdown, which can be seen for the mean reversion strategies and the training set strategy (Time count in the range 400 to 600) is from mid-2015 to mid-2016. The SPDR prices have fluctuated a lot between \$210 to \$180 during that time, which is also evidenced from the volatility initially peaking at 8 units in the figure. However, the crossover strategies didn't have a high increase in drawdown compared to mean reversion strategies in that period, which could be because the crossover strategies focus more on long-term trends rather than short-term mean reversion.

Mean and Standard Deviation of the Average Excess Returns of Strategies and SPDR

Comparison of performance of strategies, solely on the basis of mean and standard deviation, require the optimal to have the highest mean and the lowest standard deviation. This is because, high mean allows the strategy to earn higher returns or more alpha, while its standard deviation is relatively low. In Figure 23, the SPDR excess returns, while having the least standard deviation, also has low mean. The mean reversion strategy 2 (with MA-100) and test set neural network strategy are found to have the best performance amongst all strategies. They are chosen as the mean of the avg. excess return of their strategies are significantly high, while all strategies have relatively close standard deviations. **This indicates a high potential strategy by combining the Mean Reversion SMA-100 and Test Neural Network Strategies, which is further talked on in the next section.**

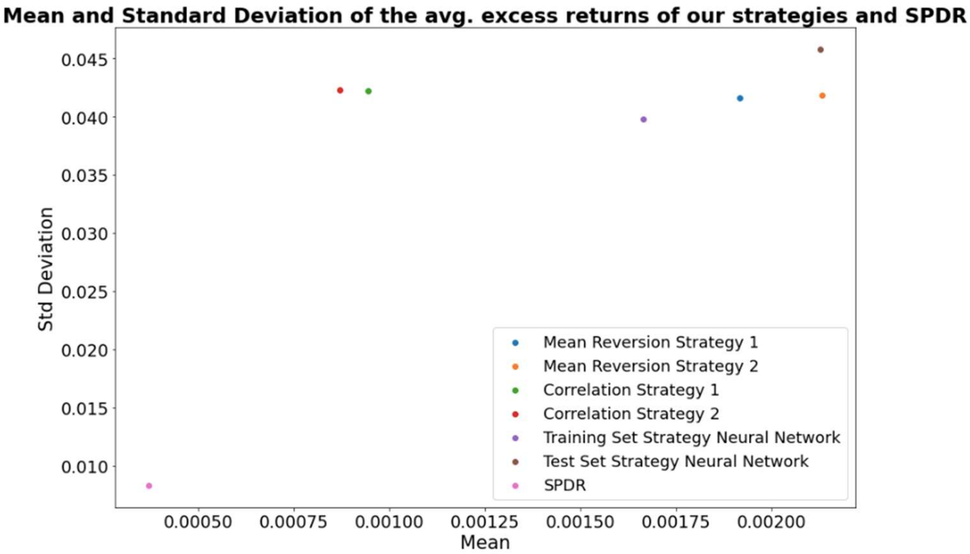


Figure 23: Mean and Standard Deviation of the Average Excess Returns of Strategies and SPDR

Discussions

Throughout the trading research carried for the 6 traditional and advanced strategies, the best performances are found to be of SMA-100 Mean Reversion Strategy and Test Set Neural Network Regressor Strategy. The mean reversion strategy resulted in an impressive performance throughout the time series in question. It created an impeccable growth in capital, especially in times of high stock volatility by accurately predicting trade signals, rather than losing significant money in high-risk times. This is evident from the strategy having the lowest maximum markdown, high Calmar ratio and significantly high mean and low standard deviation of its excess returns as discussed in the earlier section. The Neural Network Test Strategy model had produced high trading capital, equivalent to that of Crossover Strategies, in just a span of 2 years. It also had the highest Sharpe and Sortino ratios, indicating its unique ability of having a risk-adjusted performance, as compared to the other models. As discussed in the last section, there could a huge trading potential if the Mean Reversion SMA-100 and Neural Network Strategies are combined, which we explore as our 4th and "Bonus Strategy". **We work on this strategy where the first 70% days are driven by the decisions of Mean Reversion Strategies and the later 30% are driven by the fitted Neural Network MLP Regressor. This leads us to create the "Bonus Strategy" for our SPDR Trading (added an extra Jupyter Code file of it). This combined mean reversion SMA-100 and Neural Network Strategy gives an astoundingly excellent Sharpe Ratio of 3.44 and a maximum drawdown equal to -100%, which is a groundbreaking performance, especially compared to the performance of the 6 strategies we dealt with in this study.** Thus, there is a potential of combining the principles of traditional strategies in the structure of an advanced machine learning model, opening new trading possibilities in the financial markets.

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