Momentum, Market-Regime and Stocks & Options Trading Strategies.

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Abstract

This research project seeks to examine the relationship between momentum, stocks and options trading strategies. First, we examine a simple momentum trading strategy for stocks. These discussions are then extended and applied to options trading. Further, we explore how changes in economic conditions can cause trading performances to change from long-term averages and techniques that can be used to mitigate the impact of volatility and regime-shifts on trading performance.

Keywords

Momentum, Trading Strategies, Trend-Following, Options, Regime-Shift, Black-Scholes, VIX Index, Hidden Markov Model, Average True Range, Moving Averages, Straddle, Dynamic Hedging

Introduction

Momentum traders seek to take advantage of trends or patterns in the market by taking short-term buy and sell positions. However, this trading philosophy contradicts the "Efficient Market Hypothesis" and the "Theory of Random Walk" which suggests that changes in stock prices have the same distribution and are independent of each other and that past price movement or trend of a stock cannot be used to predict its future movement. But the market is not perfectly efficient, information asymmetry in the marketplace, system failures, flash crashes, human emotions, volatilities and other anomalies suggest that inefficiencies exist that could be exploited to generate alphas. Thus, momentum strategies have become popular and investors have used these strategies to make profitable returns using both qualitative and quantitative techniques to create filters, signals, position sizing, and determine the frequencies and timing of trade entries and exits.

Momentum strategies are predicated on entering a long position when the underlying is rising and a short position when the underlying is falling. According to the International Association for Quantitative Finance - IAQF (2018)[4], choosing when to long and when to short is thus primarily a filtering problem where the investor is attempting to filter or extract out trends in prices from noisy market signals. At the most basic level, a momentum strategy entails the use of a Simple Moving Average (SMA) or other technical indicators such as the Average True Range (ATR) and the Bollinger Band (BB) crossover techniques to determine buy and sell signals. While these techniques may be profitable in a stable economic regime with low volatility, they can lead to losses if there is a sudden and significant regime shift in the economy. It is a well-known phenomenon that the economic story is a cyclical one and that it oscillates between low-volatility state characterized by growth and high-volatility state characterized by contraction.

In this project, we explore different momentum strategies for stocks and options and then examine how we can leverage mathematical models to develop strategies that are immune to changes in economic conditions (or that are at least less susceptible to losses due to changes in economic regime) while generating profitable returns or alpha. Specifically, we explore the use of Markov-Switching models such as the Hidden Markov Model (HMM) to forecast highly volatile periods and take these forecasts into account in building our trading signals. The research exercise employs a case study approach and constructs momentum trading strategies for both stocks and options and presents the related key performance indicators (KPIs) for the different strategies. Please note that some of the strategies discussed in this research project closely follow the IAQF students' competition for 2018.

Data & Development Environment

The supporting programs and systems were developed using the Python programming language (Version 3.6) and input data were downloaded from Yahoo Finance where possible as in the case of stock prices or calculated as in the case of historical option prices using the Black-Scholes model. The analysis covers S&P prices for the period between January 1, 2007 and November 20, 2018. The Anaconda Integrated Development Environment (IDE) was utilized for building the software programs. All supporting programs are available on the internet in a git repository.

Trading, Regime-Shift & Volatility

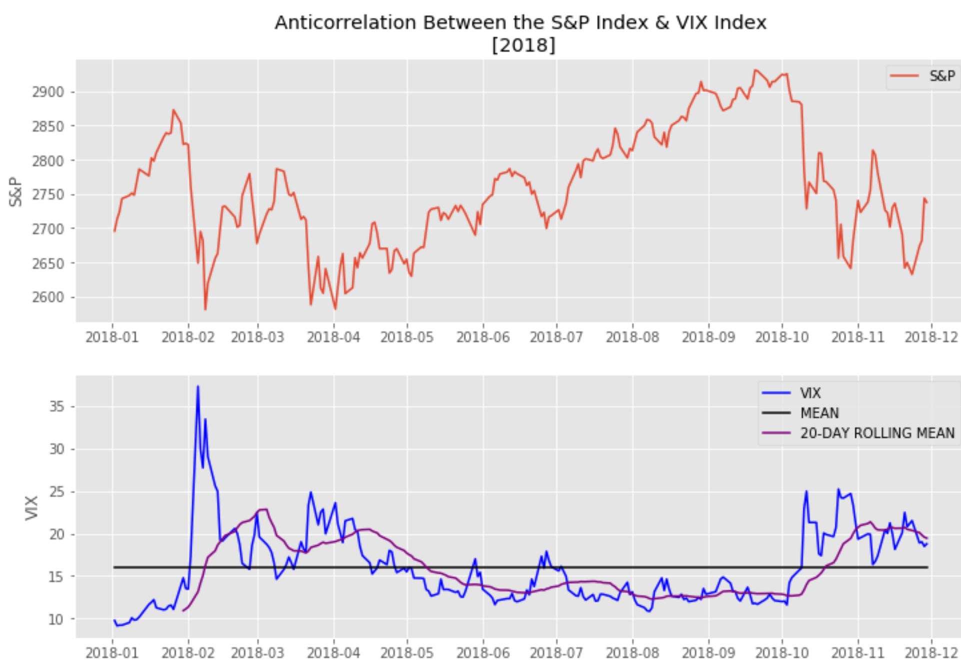
An investor can choose to buy and hold a security for the long-term without actively managing the portfolio. In this case, the cumulative return on the investment is the amount earned between when it was bought and when it was finally disposed. Conversely, an investor may follow trends and momentum in the market and repeatedly buy and sell a security using one of many trend-following strategies. In this case, the cumulative return on the investment is the return on the asset from when it was bought till when it was finally sold plus or minus the profit and losses on the swing trades - these returns form the basis for determining the performance of the investment strategy vis-a-viz alternative strategies or a benchmark buy and hold approach. The extent to which the performance of the momentum trading approach surpasses those of alternative methods is thus a good indicator of its efficacy all things being equal.

However, momentum strategies are not always profitable. Sudden changes or reversals in a trend can lead to significant losses. A key challenge for momentum traders is thus the need to constantly track the up and down movements in the market . For instance, a stock that is currently trending upward can suddenly reverse and starts to move in a downward trajectory due to changes in macroeconomic variables such as inflation, interest rate, unemployment numbers and other regulatory and government policies. There is therefore the motivation for traders to detect and affect their trading signals, position sizing and frequencies of entries and exit to mitigate the impact of volatility resulting from regime-shift. Hence, the use of stop losses or regime-shift detection techniques such as the HMM can help mitigate but not totally eliminate such losses.

One of the methods traders use for tracking volatility in the market is a technical indicator known as the "Volatility Ratio" (VR). The VR is a measure that helps traders identify volatility in stock prices and when combined with macroeconomic data such as unemployment rate or Consumer Price Index (CPI) can be used to potentially mitigate the impact of regime-shifts. The VR calculated is usually compared with a macroeconomic data or two to enter trading positions. For instance, if the difference between the VR and a macroeconomic variable is greater than a threshold, enter into a long position or a short otherwise. This threshold is usually determined using an optimization technique - an iterative process that repeatedly loops through an objective function in order to find the parameters that maximizes a particular outcome.

Regime shift in the economy can also be tracked by monitoring the VIX index. According to the Chicago Board of Exchange (2018)[1], the VIX Index is a calculation designed to produce a measure of constant, 30-day expected volatility of the U.S. stock market, derived from real-time, mid-quote prices of S&P 500 Index call and put options. Lehman (2018)[5] noted that the market can be categorized into two states - Risk-on/Risk-off. Risk-on regime is categorized by low volatility, low correlation between instruments, high returns and high return to volatility ratio. Risk-off regime on the other hand is categorized by high volatility, low returns, low return to volatility ratio and high correlation between asset classes and instruments. Lehman (2018)[5] noted further that the VIX Index is inversely correlated with the market i.e. the S&P Index and that the VIX is mean reverting so that when it goes up too much or comes down too much, it eventually reverts to the mean from the extremes. Investors should therefore go long when the VIX is too high and short equity when it is too low.

Figure 1. Anticorrelation Between the S&P Index & VIX Index 2018



How then can one determine extreme values? One way is to use the moving average method - a more than 10% difference between today's value and the 10-day moving average could be indicative of a significant change in the VIX index. Another approach is to use the Relative Strength Indicator (RSI) normalized to a range between 0 and 100 - a range of between 30 and 70 is considered normal. This indicator can be calculated using the formulae below Lehman (2018)[5]:

$$\text{Indicator} = 100 * [\text{1-1+(UpCloseAvg/DnCloseAvg)}] \tag{1}$$

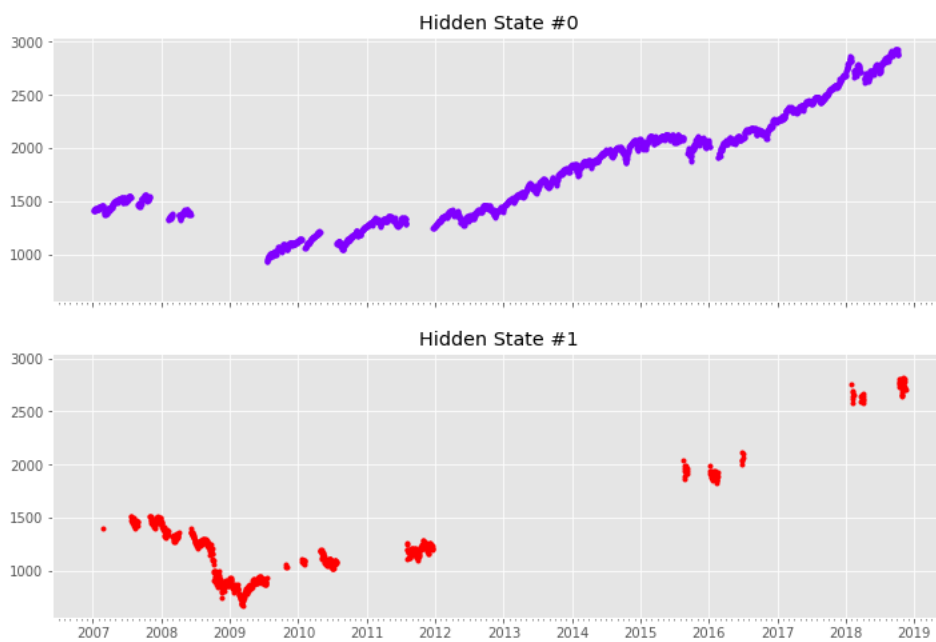
$$\text{UpCloseAvg} = \text{EMA(Max[delta(Close),0])} \tag{2}$$

$$\text{DownCloseAvg} = \text{EMA(Min[delta(Close),0])} \tag{3}$$

Lehman (2018)[5] noted further that another way by which the VIX can be used to generate trading signals is by monitoring the VIX Futures Curve. Generally speaking in a contango, the curve has a positive slope because the market believes that volatility may rise and hence it is willing to pay a price to hedge security positions. Conversely, in a backwardation, the curve is experiencing a negative slope. This usually occurs when the market expects volatility to revert and therefore is a good time to buy because when volatility falls prices go up.

Another method for detecting regime-shift, which is the main thrust of regime-shift/volatility detection technique discussed in this essay is the HMM model. According to QuantStart 2018[6], these models are well suited for detecting regime shift as they involve inference on "hidden generative processes" via "noisy" indirect observations correlated to these processes. QuantStart 2018[6], stated further that this hidden or latent process is the underlying regime state while the asset returns are the indirect noisy observations that are influenced by these states. As can be seen in the chart below, hidden state 0 represents periods of low volatility and period state 1 represents periods of high volatility, these information should therefore be taken into into consideration for risk management purposes specifically to affect the trading signals. This research paper uses only this method for detecting regime shift for the different trading strategies. It is worthy to note that for all the strategies considered, trading cost and fees are ignored.

Figure 2. HMM Plot of the S&P Between 2007 and 2018



In order to mitigate the impact of volatility due to regime-shift on the strategies implemented in this research project, we affected our trading signals by the signals generated from the HMM model. For instance, if the SMA signals a buy, we ignored this signal if the HMM indicated that we are in a volatile regime. Though many momentum trading strategies exist for stocks, this research project only discusses the implementation of the SMA strategy for stocks trading. In addition, we focused on the application of the model for predicting regime-shift and affecting our trading signals and less on the mathematical underpinnings of these models. Specifically, we relied on Python libraries such as HMM learn and Mibian to implement the model in our trading system.

Momentum Trading Strategies for Stocks

Having established some background on stock trading and the impact of volatility on their efficacies, we now discuss the implementation of a simple SMA as outlined below. Please note this implementation makes many simplifying assumptions. For instance, we have unlimted cash balance to enter into buy and sell positions and there are no transaction costs, fees, slippages, gap ups and gap downs.

Portfolio 1 - Use the S&P500 Index and Construct the Daily Time Series of a Momentum Strategy as follows:

- If the 10-day moving average price of the index is greater than the 50-day moving average price the position is long one unit of the index.
- If the 10-day moving average price of the index is less than the 50-day moving average price the position is short one unit of the index.
- Use the HMM to forecast periods of high volatility and use the information generated to affect your trading signals. If the HMM signals high volatility, pass on trading even if the SMA signals a buy and sell only if the HMM signals a highly volatile regime.
- Compare and contrast the Key Performance Indicators (KPIs) for these strategies to a Buy & Hold technique.

KPIs & Charts for Portfolio 1 - Simple Moving Average Crossover Technique

An SMA is the unweighted mean of the previous n-day closing prices. When calculating successive values, the oldest value is dropped from the calculation and a new value is added into the calculation. An alternative to the SMA is the exponential moving average (EMA). The SMA is calculated as follows:

$$\text{SMA} = \frac{PM + PM_{-1} + ... + PM_{-(n-1)}}{n} \tag{4}$$

where PM is the stock closing prices and n is the number of days in the SMA window.

The SMA strategy outperformed the Buy & Hold strategy with cumulative returns of 52.3% and 73.2% respectively. However, the SMA with HMM outperformed plain-vanilla SMA strategy with a cumulative return of 85.6%. The KPI covers S&P stock prices from January 1, 2007 to November 17, 2018. This strategy could also have been designed to exit our entire position if a highly volatile regime is detected rather than just passing on new trades and keeping the existing positions. Other KPIs relating to these strategies are shown in Table 1 below.

Figure 3. 10dSMA Versus 50dSMA - Position Sizing

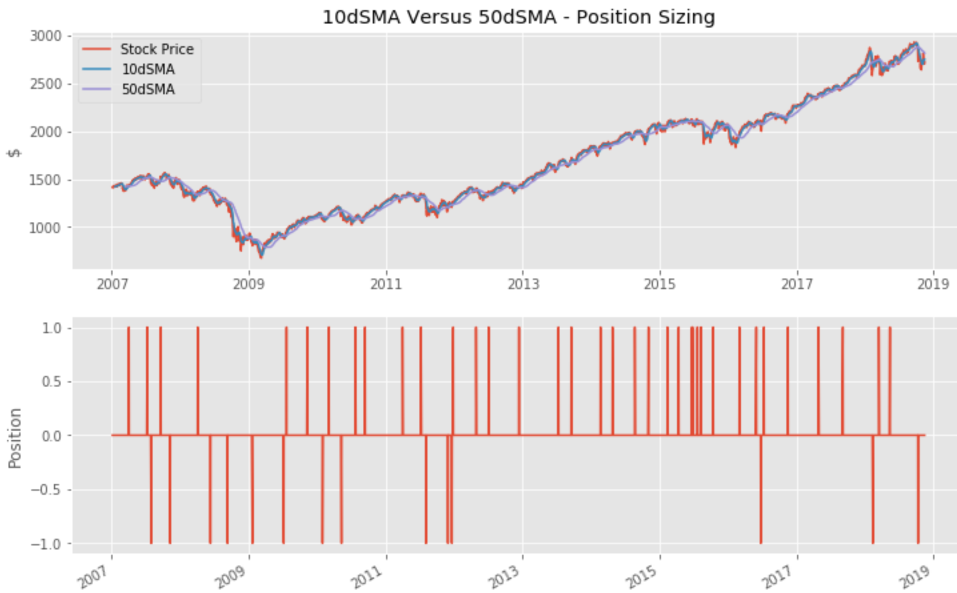


Figure 4. Cumulative Returns - CrossOver Strategy Versus Buy & Hold

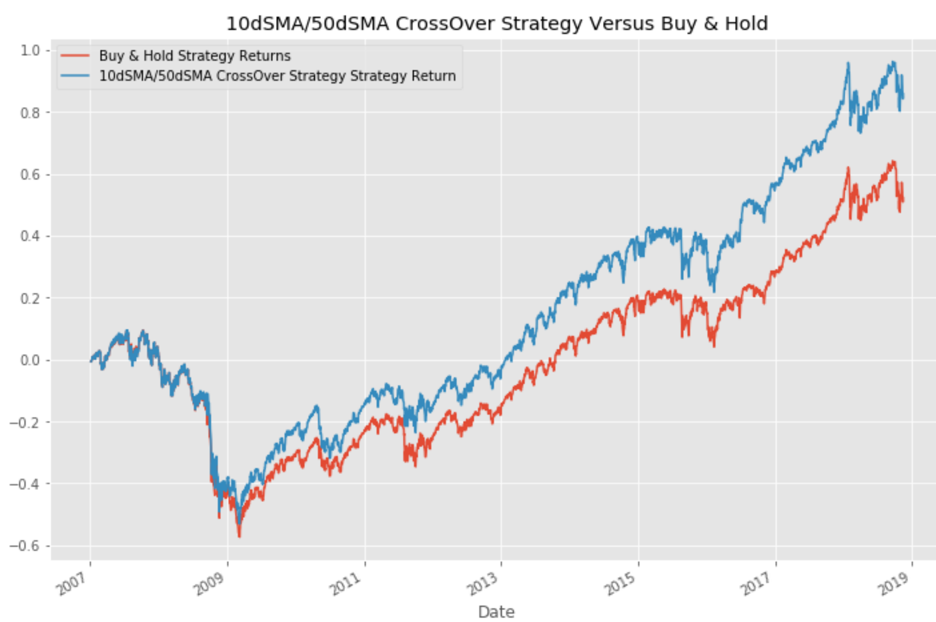
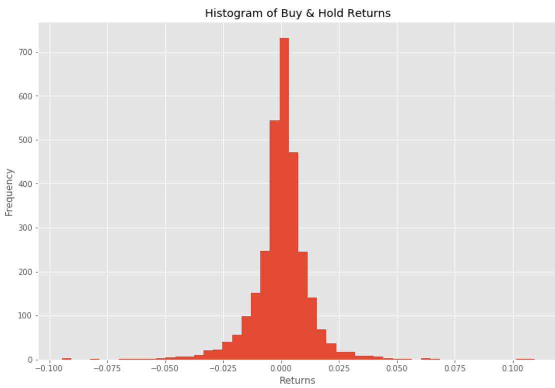


Figure 5. Histogram of BH & SMA with HMM Returns

(a) Buy & Hold



(b) SMA with HMM

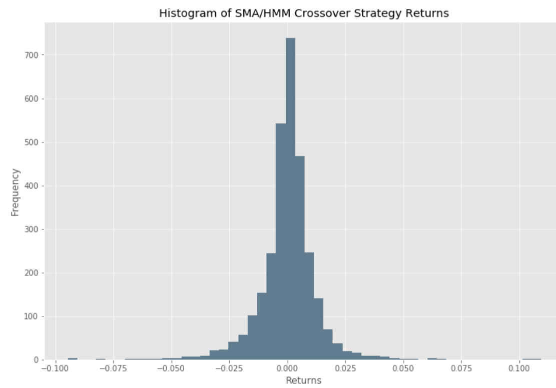


Table 1. KPIs for Buy & Hold (BH), SMA & SMA with Hidden Markov Model

Description	BH	SMA	SMA with HMM
Annualized Return	0.055	0.066	0.072
Annualized Std Dev	0.198	0.197	0.196
Average Monthly Return	0.005	0.005	0.006
Avg Loss Return	-0.008	-0.008	-0.008
Average Win Return	0.007	0.007	0.007
Gain to Pain Ratio	0.000	0.000	0.000
Lake Ratio	0.178	0.146	0.124
Loss Rate	0.458	0.451	0.455
Max Drawdown	-0.610	-0.581	-0.572
Monthly Drawdown	-0.289	-0.289	-0.289
Sharpe Ratio	0.279	0.334	0.365
Trade Expectancy	0.008	0.008	0.008
Win Rate	0.542	0.549	0.545

Momentum Trading Strategies for Options

An option is a derivative instrument that derives its value from the underlying stock security. It gives the holder the right but not the obligation to buy or sell a particular number of the underlying stock at a specified strike price on or before the options expiration date. An option can either be a European option which can only be exercised at maturity or an American option which can be exercised on or before expiration. A European option can be priced using a Black-Scholes model but an American option has to be valued using an interest rate tree. To keep things simple, the prices of options used in this research project were calculated using the Black-Scholes (BS) model. The price of a stock option that pays no dividend can be calculated using the BS formulae below (Rouah & Vainberg (2007)[2]:

$$C(S_t, t) = N(d_1)S_t - N(d_2)Ke^{-r(T-t)} \tag{5}$$

$$P(S_t, t) = N(d_2)Ke^{-r(T-t)} - N(d_1)S_t \tag{6}$$

$$d_1 = \frac{1}{\sigma\sqrt{(T-t)}}\left[\ln\left(\frac{S_t}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)(T-t)\right] \tag{7}$$

$$d_2 = d_1 - \sigma\sqrt{(T-t)} \tag{8}$$

where $C(S_t, t)$ and $P(S_t, t)$ are the value of the call and put options respectively, $N(.)$ is the cumulative distribution function of the standard normal distribution, $T - t$ is the time in years, K represents the strike prices, $-r$ is the risk free rate and σ is the volatility of the returns of the underlying assets .

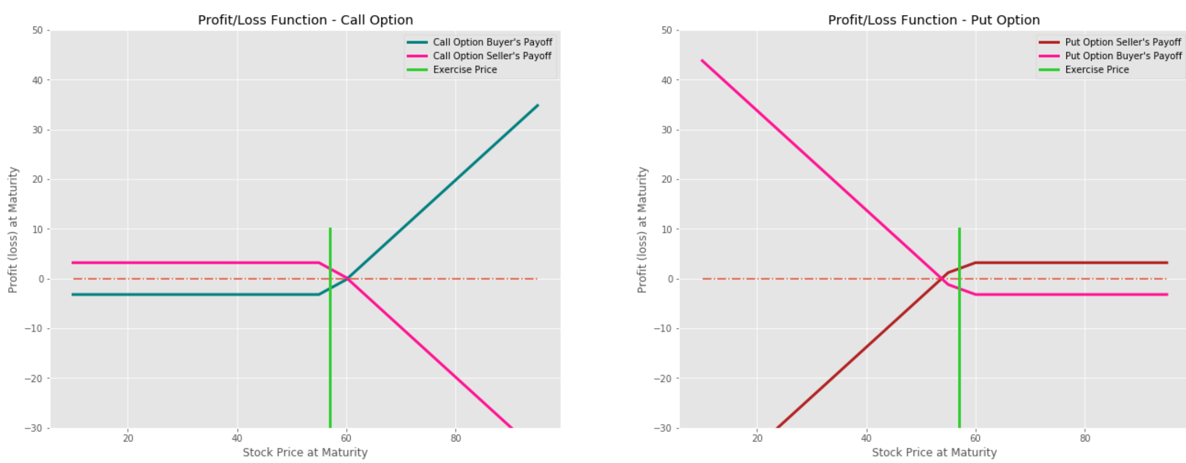
In addition to the above formulae, the payoffs for the options and the corresponding returns (percentage basis) on trade exits are calculated as follows:

$$\text{Short Put Payoff} = \text{Max(Strike - Stock Price, 0)} \tag{9}$$

$$\text{Short Call Payoff} = \text{Max(Stock Price - Strike, 0)} \tag{10}$$

Figure 6. Pay Off Diagrams for Call & Put Options

(a) Call Option **(b)** Put Option



$$\text{Short Put Return} = \frac{\text{(Premium - Short Put Payoff)}}{\text{Short Put Payoff}} \tag{11}$$

$$\text{Short Call Return} = \frac{\text{(Premium - Short Call Payoff)}}{\text{Short Call Payoff}} \tag{12}$$

Portfolio 2 - Using Black-Scholes Construct a Daily Time Series of the Returns of Portfolios of At-The-Money Puts and Calls (90 day horizon) to Match the Time Series of the Moving Average.

Construct a daily time series of the returns of portfolios of at-the-money puts and calls (90 day horizon) to match the time series of the moving average using the Black-Scholes model to keep things simple. For example, if for a call portfolio we sell a call at the close of day 0, and then buy that call at the end of day 1 that would be the return for day 1. We then sell a new call at the end of day 1 and buy that call at the end of day 2 that would be the return for day 2 :

- If the 10-day moving average price of the index is greater than the 50-day moving average price the position is Short one call.
- If the 10-day moving average price of the index is less than the 50-day moving average price the position is Short one put.
- Use an HMM to forecast periods of high volatility and use the information generated to affect your trading signals. Calls are only sold if the HMM predicts a volatile regime and puts are only sold if the HMM predicts a less volatile regime.
- Compare and contrast the Key Performance Indicators (KPIs) for these strategies to a Buy & Hold technique.

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KPIs & Charts for Portfolio 2 - Short Call Short Put with HMM Crossover Technique

To implement this strategy, the values for both the ATM put and call options were calculated using the Mibian Python library for pricing options and saved in a dataframe. The strike prices were then shifted forward by one day since strike prices remain constant and our expiration is one (1) day. This information is then combined with the adjusted closing prices at expiration to calculate the option pay offs. In addition, we created two separate portfolios, one for the short put and the other for the short call and then combined the returns from the two sub-portfolios to get the total cumulative returns for the strategy. Recall that we only entered a short call if the faster moving average is greater than the slower moving average. Therefore, on the day that we entered a short call we cannot not also enter a short put. So we need to combine the results from the two sub-portfolios to get the aggregate return for the strategy. Returns were calculated using equations (11) and (12).

We first developed the strategy without affecting our signal with the output from the HMM model and then constructed another portfolio in which we affected the trading signals with the result of the HMM model. **Please note that when running the HMM model, the signal for volatile and non-volatile regimes can flip between 0 and 1 between each run. It is therefore expedient to observe the HMM chart and update the signal flag in the functions created to generate the trading signals for both the put and call options. Please refer to Figure 2 where the volatile regime was given a flag of 1 and the non-volatile regime was given a flag of 0.** The table and charts below shows the performances of the two methodologies.

Table 2. KPIs for Buy & Hold (BH), Short Call Short Put without HMM & Short Call Short Put with HMM

Description	BH	Short Call Short Put	Short Call Short Put with HMM
Annualized Return	0.053	4035.454	4272.019
Annualized Std Dev	0.198	2306.655	2507.545
Avg Loss Return	-0.008	N/A	N/A
Average Win Return	0.007	16.014	16.953
Gain to Pain Ratio	0.000	N/A	N/A
Lake Ratio	0.178	N/A	N/A
Loss Rate	0.458	0.000	0000
Max Drawdown	-0.610	0.000	0.000
Monthly Drawdown	-0.289	0.012	0.012
Sharpe Ratio	0.279	1.750	1.704
Trade Expectancy	0.008	N/A	N/A
Win Rate	0.542	1.000	1.000

As shown in Table 2, a buy and hold strategy generated an annualized return of 5.3% per annum and the Short Call Short Put strategy generated a whopping 403,546% return while the Short Put Short Call Strategy with HMM generated an even better result of 427,202%. This result should be evaluated in context, first because of data limitations, the option prices and payoffs were calculated using the Black-Scholes model but in real life option values for American options are calculated using interest rate trees. Therefore, using real life historical option value would have generated a more reasonable return. In addition, returns were calculated using equations (11) and (12) and the formulae for calculating returns may differ from one research project to the other. Therefore, the formulae for calculating profits and losses on options should be agreed upon at the outset. Another reasonable approach is to start out with a specific sum say $1,000,000 USD at the outset and then use that amount and the closing balance at the end of the investment period as the basis for calculating the investment performance . The Capital-at-Risk could also be considered as the cost of consummating the transaction. For example, to short a put on a stock, the seller could potentially lose a lot of money if the price were to go to zero, the potential amount that the investor can lose can thus be considered as the cost of investment. Margin deposits though recoupable may also have to be considered.

In addition, transaction costs and fees were totally ignored in this implementation and given the frequency of trading if taken into account could have significantly impacted the profitability of the strategy. For instance, out Wint Rate(%) was 100%. Accounting for transaction fees and cost would have reduced this KPI.

Figure 7. Returns & Cumulative Returns for Short Put & Short Call Portfolios

(a) Short Put Portfolio **(b)** Short Call Portfolio

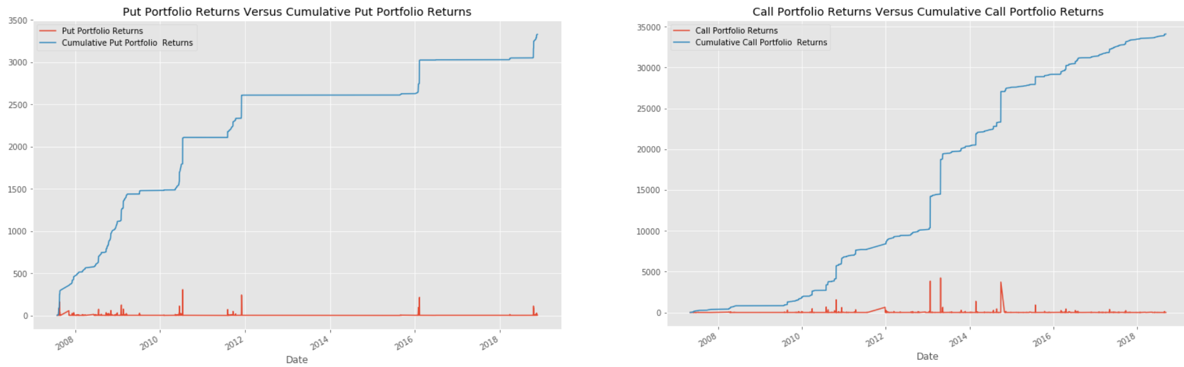


Figure 8. Combined Cumulative Return for Short Call & Short Put Portfolio

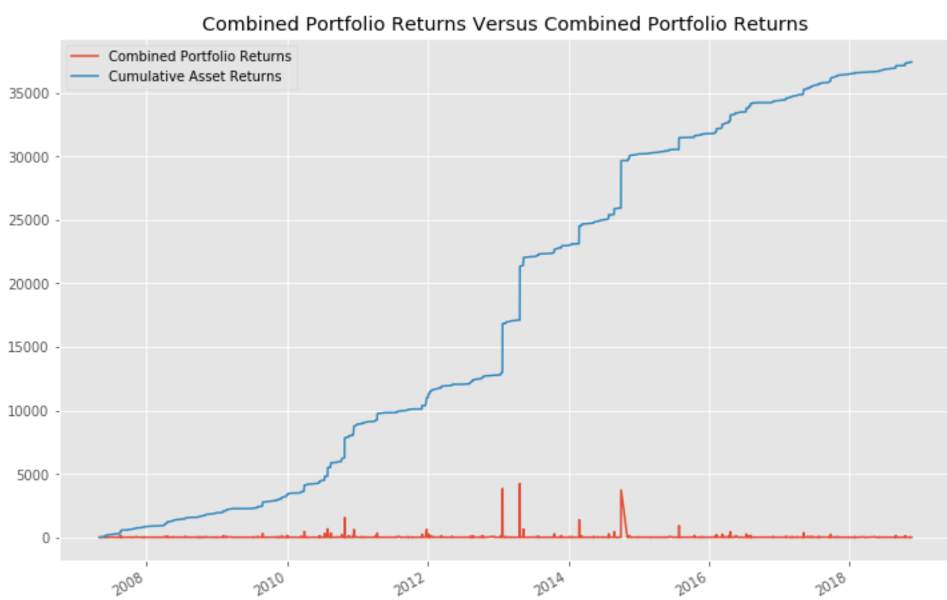
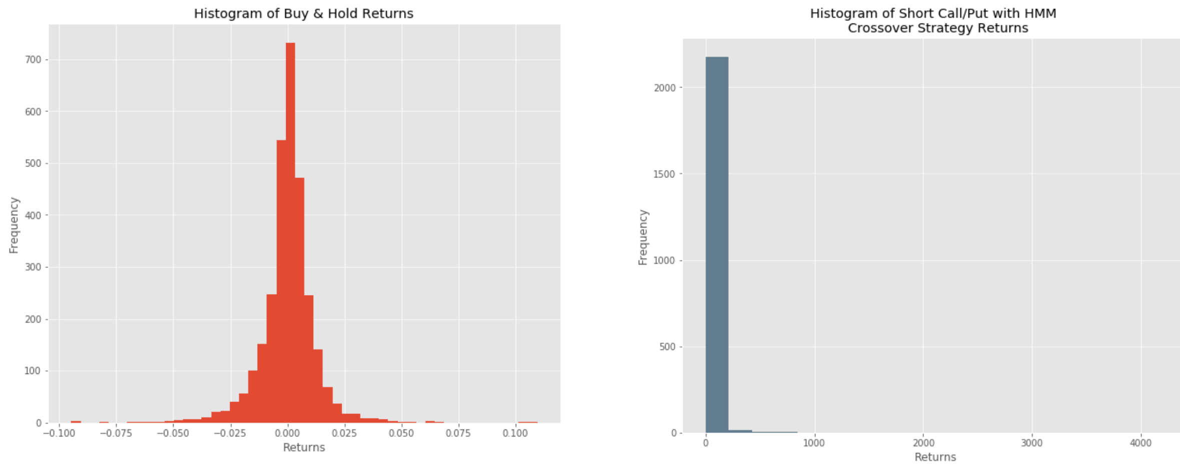


Figure 9. Histogram of Returns for BH and Short Call & Short Put Strategy

(a) Buy & Hold **(b)** Short Call Short Put With HMM Portfolio



Note that while the return of the histogram for the BH strategy appears to follow a normal distribution, the return for the Short Call Short Put strategy is right skewed with 100% Win Rate.

Portfolio 3 - Redesign Portfolio 2 Using At-The-Money Straddles as the Underlying instead of Plain-Vanilla Puts and Calls

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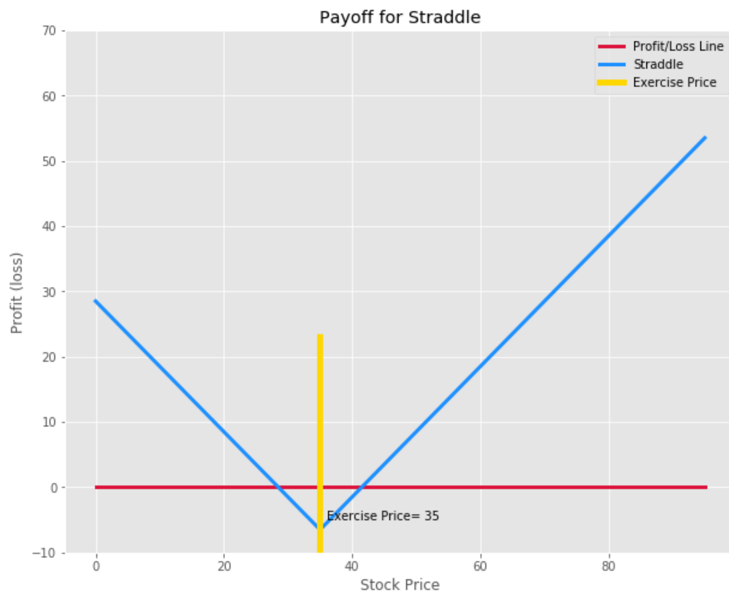
A straddle is a volatility trading strategy that only makes money when the underlying becomes volatile and moves significantly in either direction and losses money otherwise. An ATM straddle is a strategy in which the investor holds a position in both a call and a put with the same strike price and expiration date.

To implement this strategy the price of a straddle expiring in 90 days is calculated using the Mibian Python library. The strike prices are then rollforward or shift by one day in order to ma to the current close prices on day 1 because they remain constant. A new price is calculated using an expiration of 89 days at the strike price and new closing price. The difference between the two prices is then taken as the gain or loss on the transaction. This method is akin to using the opportunity cost of entering a new position to close an existing one as the value of the derivative on the date on which the position was closed. This is a simplifying assumption made to make the implementation easier. Of course, the alternative would is to calculate the payoff on the next day and then take that as the exit price. That said, this prototype can easily be extended to use the second method.

Figure 10. PayOff Diagram for a Long Straddle Position



KPIs & Charts for Portfolio 3 - Long Straddle Crossover Technique with & without HMM

As stated earlier, a straddle is a volatility play and will return profit when the underlying is more volatile than when it is not. Therefore, a strategy that is set to only enter long straddles when the underlying is in a volatile regime performed better than the one set to enter long straddles when the underlying is less volatile. The table below shows the KPIs of different simulated long straddle strategies:

Table 3. KPIs for Long Straddle, Straddle with Low Volatility & High Volatility

Description	Straddle	Straddle Low Volatility	Straddle High Volatility
Annualized Return	4.187	2.758	5.721
Annualized Std Dev	1.153	0.998	1.293
Average Monthly Return	0.413	0.257	0.602
Avg Loss Return	-0.033	-0.032	-0.034
Average Win Return	0.059	0.046	0.073
Gain to Pain Ratio	0.654	0095	6.811
Lake Ratio	0.165	0.358	0.108
Loss Rate	0.459	0.449	0.471
Max Drawdown	-0.675	-0.725	-0.675
Monthly Drawdown	-0.573	-0.535	0.012
Sharpe Ratio	3.631	2.762	4.426
Trade Expectancy	0.047	0.039	0.054
Win Rate	0.541	0.551	0.529

The first column represents the KPIs for a straddle strategy in which the HMM signal was not taken into consideration. The second and third columns represents the KPIs for straddle strategies played in low and high volatility environments respectively. As shown in the table, the straddle strategy implemented to enter long positions in volatile environment had the best performance, because a straddle like its cousin, strangle is a volatility play and is more like to return profits when the underlying stock is volatile. Conversely, the strategy designed to enter long positions during less volatile periods performed the worst whiile the one designed to ignore the HMM signals has a performance that is in between the results generated by the other two. Other KPIs relating these strategies are shown in Table 3 above.

Figure 11. Cumulative Return for Long Straddle Strategy

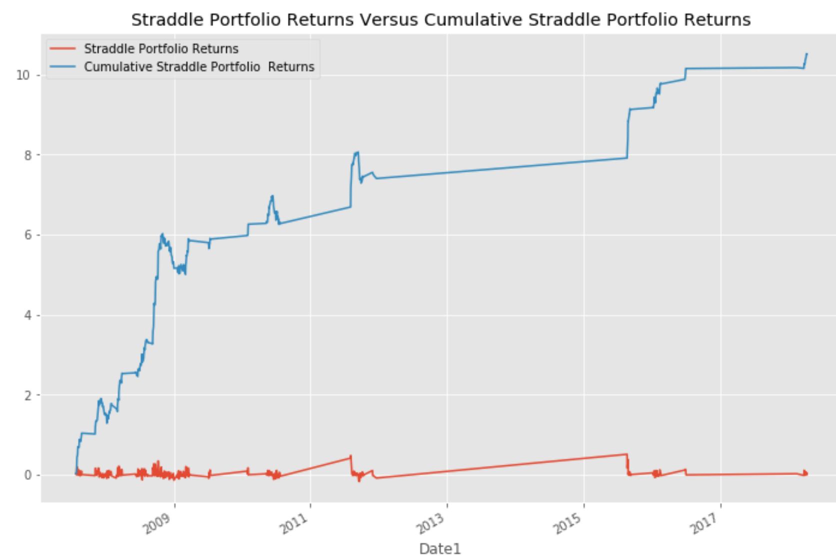
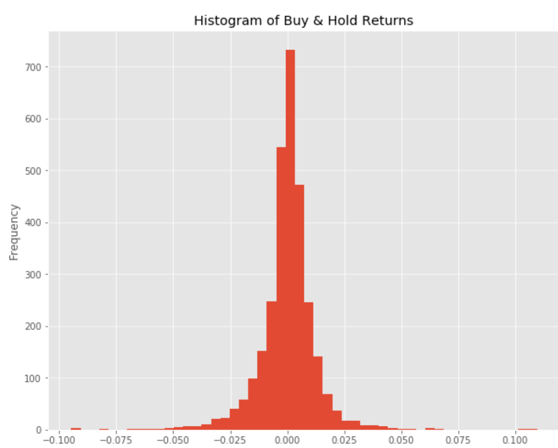
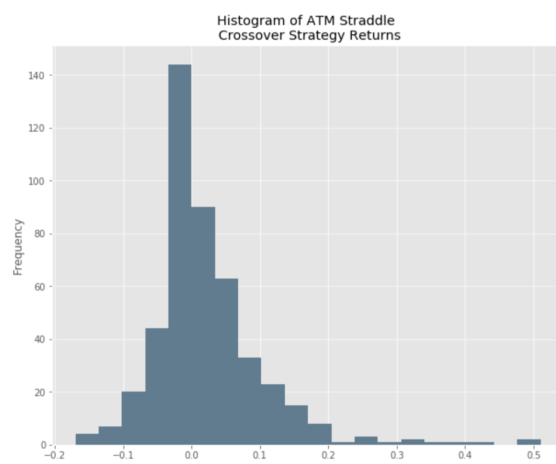


Figure 12. Histogram of Returns for BH and Long Straddle with High Volatility HMM Indicator

(a) Buy & Hold



(b) Long Straddle High Volatility



Portfolio 4 - Dynamically Hedged & Rebalanced At-the-Money Straddle

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Dynamic Hedging is a technique that is widely used by derivative dealers to hedge exposures to greeks - delta, gamma, vega or theta exposures. An example of dynamic hedging is delta hedging of a non-linear position using linear instruments like spot positions, futures or forwards. The deltas of the non-linear position and linear hedge position offset, yielding a zero delta overall. However, as the underliers value moves up or down, the delta of the non-linear position changes while that of the linear hedge does not. The deltas no longer offset, so the linear hedge has to be adjusted (increased or decreased) to restore the delta hedge. This continual adjusting of the linear position to maintain a delta hedge is called dynamic hedging (Holton 2013)[3].

Note that for this strategy, there is no need to affect the trading signal with the HMM factors, because this is a hedging strategy and not a speculative play and regardless of whether the economy is in a volatile or non-volatile regime, we want to hedge our net exposure to a particular greek to zero and as such we cannot pass on a trading at any time since the portfolio needs to be rebalanced on a daily basis. This strategy also assumes that we own the underlying asset so to delta hedge the underlying we have to short the straddle position. The payoffs for the straddles on exit were calculated using equation (7) below:

$$Straddle = (abs(sT - k) + sT - k)/2.0 - cP + (abs(k - sT) + k - sT)/2.0 - pP \tag{13}$$

where Straddle is the value of the straddle, sT is the stock price, K represents the strike prices, cP is the call premium and pP is put premium.

To this end, we construct an ATM straddle at the beginning of the moving average time series and dynamically hedge that portfolio on a daily basis so it is equivalent to an ATM straddle each day. First we generate the daily time series of returns associated with the straddle strategy, rebalancing each time at option expiration:

- Given the spot price of S&P at close on the last day of trading before the current Monday, we calculate the initial delta of the short straddle position. This initial delta would provide an estimate of the overall risk exposure of the short option position.
- To delta hedge the short straddle, we calculate the number of S&P futures contract (earliest expiry) a trader needs to buy/sell at the beginning of Trading on Monday. The idea is that the deltas of the short option and the short stock would cancel, yielding an overall delta of zero.
- We then track the underlying spot price once every day and continue the dynamic hedging process for 10 years.
- We then compare and contrast the Key Performance Indicators (KPIs) for these strategies to a buy & hold technique.

KPIs & Charts for Portfolio 4 - Dynamically Hedged & Rebalanced ATM Straddle

The KPIs for this strategy versus a BH are shown below. Note that our return for the ATM straddle is calculated based on the change in the value of our underlying asset plus or minus the effect of the premium we received for selling the straddle positions:

Table 4. KPIs for Dynamically Hedged Straddle

Description	BH	Dynamically Hedged Straddle
Annualized Return	0.051	0.150
Annualized Std Dev	0.199	0.424
Avg Loss Return	-0.009	-0.010
Average Win Return	0.007	0.009
Gain to Pain Ratio	0.000	0000
Lake Ratio	0.180	0.215
Loss Rate	0.458	0.459
Max Drawdown	-0.610	-0.628
Sharpe Ratio	0.256	0.353
Trade Expectancy	0.008	0.010
Win Rate	0.542	0.541

The dynamically hedged short straddle strategy generated an annualized return of 15% outperforming the performance of the BH with an annualized return of 5.1% though the standard deviation of returns for the hedging strategy was higher than that of the BH method . Other KPIs relating to these two strategies are shown above.

Figure 13. Net Exposure for Short Straddle Strategy

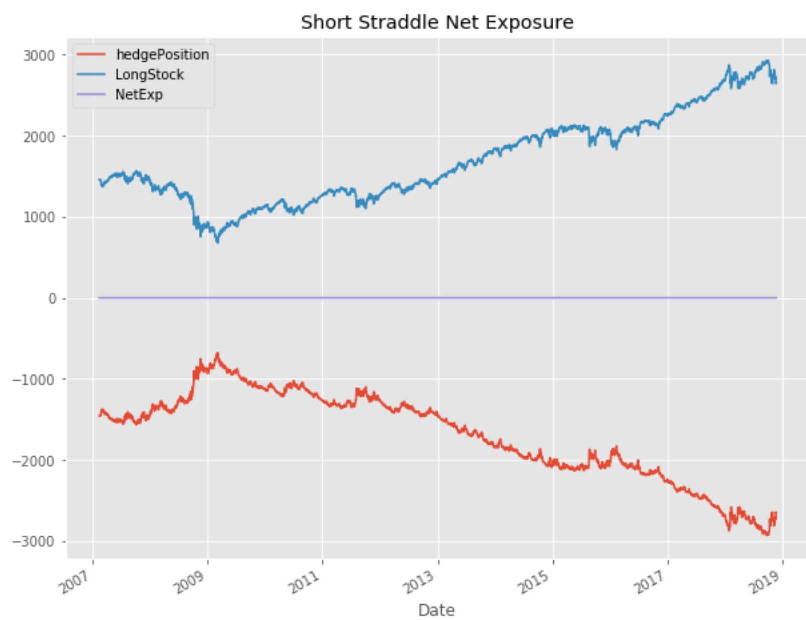


Figure 14. Cumulative Return for Dynamically Hedged Short Straddle Strategy

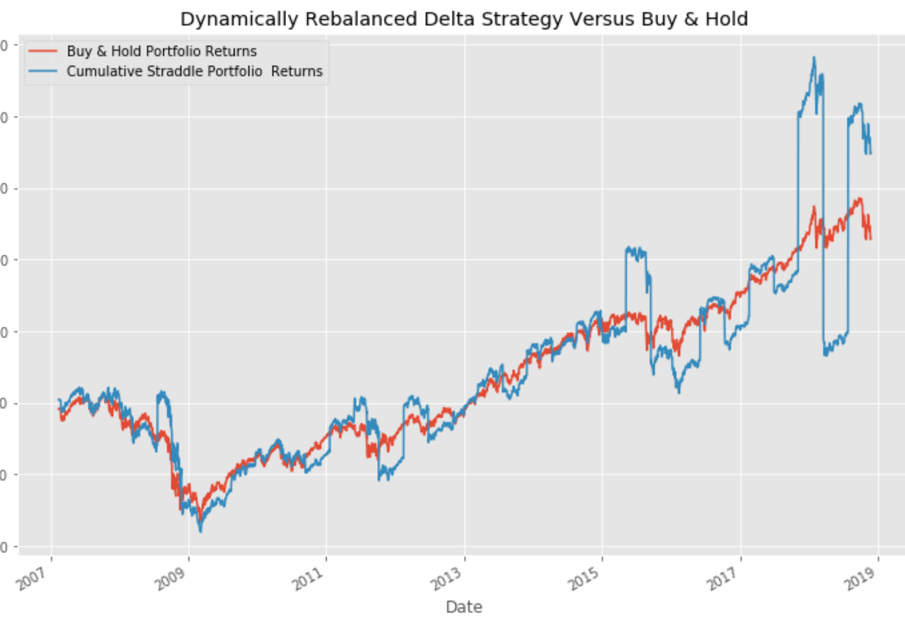
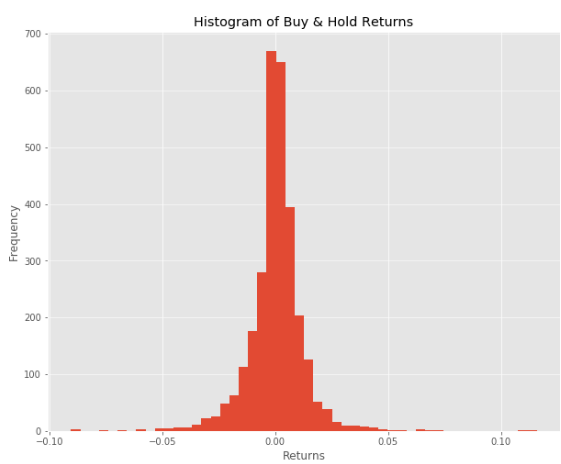
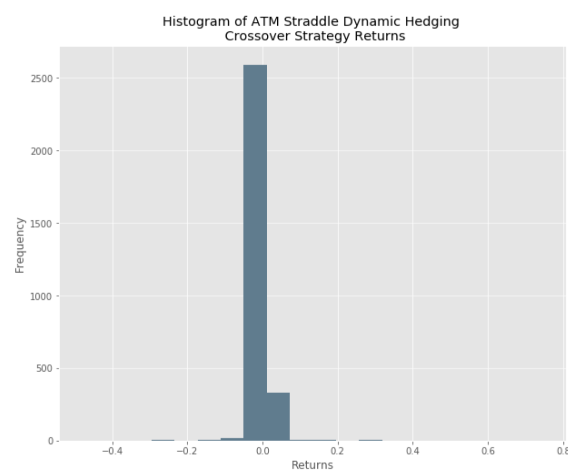


Figure 15. Histogram of Returns for BH and Dynamically Hedged ATM Short Straddle

(a) Buy & Hold



(b) Dynamically Hedged ATM Short Straddle



Conclusion

This research project explores the relationship between momentum, stocks & option trading strategies and the impact of regime-shift on trading profitability. Based on our findings, losses are generally curtailed when tradings are done in a less volatile regime except in the case of straddles which are only profitable in highly volatile regimes. The project was ambitious in terms of its scope as each of the strategies or subtopics discussed could have been the focus of an entire research project. Yet we have only scratched the surface of momentum trading strategies for stocks & options in general.

The project was limited by lack of free historical options data. In addition, options prices were calculated using the Black-Scholes model whereas interest rate trees are more appropriate for pricing American options because they can be exercised prior to maturity. A number of of simplifying assumptions were made to make the implementations easier and we only focused on one regime-shift prediction model - HMM. Using real-life options data would have significantly enhanced this research work and aligned the conclusions reached with real-life outcomes. That said, the prototypes built in this research exercise are great and can form the foundation for more robust systems in the future if the limitations noted above are addressed.

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