Comparison of Stock Market Strategies

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March 14, 2025

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Abstract

This paper aims to explore different methods for buying and selling stocks and index funds. By back testing methods involving moving averages, trend following, RSI, standard deviation, and simple buy and hold strategies, we can compare the cumulative profits and Sharpe ratios by simulating performance on historical stock movements. By taking these results and comparing them to those same strategies' performances on unseen stock data, we can evaluate how they might perform in the active stock market. While machine learning models are increasingly common in the investing world, these automated but manually modeled trading strategies are useful for retail traders without the ability to conduct high frequency trades. Additionally, regression models can be prone to being too specific to the training data, while a manually coded strategy follows a simpler logic. I conclude that the results often depend on the volatility of the stock itself, rather than one method being objectively superior in all cases.

Introduction

Shortly after the NYSE was started in 1792, people began trying to "beat the market". Predicting stock movements has been a goal of institutional investors, and in recent years, retail traders as well. And yet, nearly all investors fail to consistently beat the market (Perry), meaning simply purchasing and holding an index fund almost always yields higher results than actively trading based on various metrics.

This has led to many successful long-term investors, such as Warren Buffet and John Bogle, to push for buying and holding over the long term. They advise that this is the best strategy for most people. And, when looking at the sheer number of people who fail to beat the market every year, this is true. However, this has not stopped professional investors from making billions through various trading strategies every year. In recent years, hedge funds have taken advantage of the rising capabilities of AI and machine learning to earn billions of dollars. In this paper, I plan on evaluating which strategies tend to outperform simple buy and hold strategy using Tesla stock.

I used Yahoo Finance as my source for historical stock data. My data consists of all closing prices of Tesla between January 2012 and December 2019, with 2019 being held from the training stage to be used for testing the most successful strategies. This time range is beneficial for trading because it is large enough to include the normal movement of the economy without any large shocks, such as the 2008 recession or the 2020 Covid-19 market dip. Since these are unusual events that can throw off a strategy in the testing stage, I chose to leave them out of the process.

Using Python, I pulled the data from Yahoo Finance and programmed various strategies. As a baseline, I programmed the results of a typical buy and hold strategy, where the stock is purchased and held for the entirety of the testing period. Next was a strategy where, if the stock went up, the next day a position was opened. This was held until the stock went down, and the next day the position was closed. I followed with a mean reversion process and a trend following process, two strategies explored by Beluská in his research "Revisiting Trend-following and Mean-Reversion Strategies in Bitcoin". Instead of using a similar process to Beluská's, which was based on min/max filters, I focused on a combination of moving-averages and stop-loss thresholds (Beluská). Finally, I tested an RSI tracking method. Comparing all of these to the baseline method and to one another through profits and Sharpe ratios allows us to make hypotheses about the performance of these strategies on unseen stock data.

Literature Review

Analysis of stock market investment strategies

The first paper I read was by Graham Pentheny from the Worcester Polytechnic Institute. I wanted to see the process of more fundamental, business-driven investment strategies. Since the investing world has become more automated than at any time in the past, it is useful to consider the benefits of looking inward on companies' product launches, revenue streams, and other more grounded methods of evaluating whether a stock is over or undervalued. Models and statistical strategies are beneficial and can uncover trends that investors may not notice, but there will always be a need for a more human decision-making process.

Pentheny discusses his thought process during simulated day-trading. He focuses more on a business's news and whether he thinks investors have it wrong, than trying to guess where the stock's price will move next. For example, he decided to purchase Ford stock due to its low-price fluctuation and low relative cost. By actively watching for movements and making conscious decisions about many different stocks, he was able to make a profit and reach his trading goals.

While this information is important and exposes the potential success of less data driven and more intuitive trading, I think this kind of investing is more suited for retail investors with moderate amounts of money in the market. In today's world, if someone were to take a less quantitative approach like this and try to compete at the level of hedge funds, they would not be able to perform their trades quickly enough. Algorithmic trading has dominated the day-trading world because automated trades can execute in an instant. There will always be a place for fundamental trading, but for longer term positions based on the intrinsic value of the company, rather than trying to ride the upswings and avoid the downfalls.

Prediction of Stock Performance by Using Logistic Regression

The second paper I reviewed was research on a logistic regression model's performance in the Pakistan Stock Exchange. Similarly to my research, the authors wanted to employ techniques to predict stock performance. They included features such as "sales growth, debt to equity ratio[s], book to price ratio[s], earning per share" and others (Ali 1). By focusing on accounting and financial variables, they were able to predict intrinsic value of companies, which cuts through the volatility and error of the market.

Their predicted value was a binary result that equaled 1 if the stock performance was above the Karachi stock exchange index and 0 if it was below. This allowed them to classify stocks as good or poor investments. It seems their goal was to identify valuable investments, rather than trade frequently and algorithmically. If I were ever to expand on my research in this paper, I would like to follow more closely to their process, because I do value quantitative investing based on actual business success and relative value in addition to the focus of my paper, which is on attempting to arbitrage daily stock movements.

Strategy Comparison

Strategy 1: Buy and Hold

The purpose of this paper is to see if any active strategies can outperform long-term investing. To serve as a baseline, I first programmed a strategy that buys Tesla stock and holds it for the entirety of the training period (2012-2018). Buy and hold is a conservative strategy that aims to reduce risk by taking all gains and losses of a company over a long period of time. The idea is that the average gains will be positive and the risk is low when held for a long time. According to Hui Ling from the University of Malaysia, test results seem to indicate that this strategy reduces the risk of investing in an equity, but it does not necessarily increase or decrease returns. This shows that the general theory of positive correlation between risk and returns remains true when comparing to other strategies (Ling). For this reason, I will be using the Sharpe Ratio as a risk-adjusted measure of the success of a strategy to see which strategy performs best in terms of both returns and risk.

By calculating the daily percentage return and then taking a “buy” position in every trading day, I was able to calculate the cumulative earnings by summing the daily returns over the 7-year period. I then calculated the Sharpe Ratio by taking the mean of the daily returns and dividing by the standard deviation of the daily returns. The results were as follows:

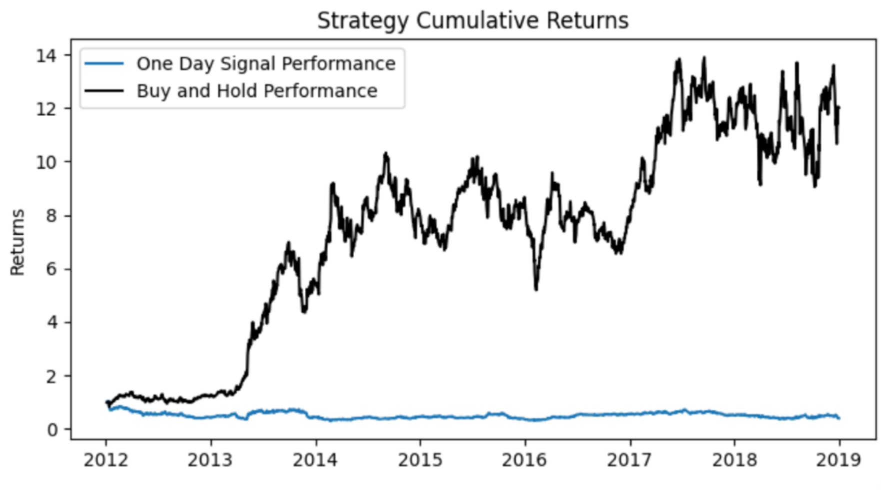
Cumulative Return: 1101.0107%

Sharpe Ratio: 0.96

The cumulative return is numerically not very important yet, as this is on training data. I will be comparing the cumulative return and Sharpe Ratios to the other methods; the method that performs the best will be applied to the test set (2019), where the result will be cumulative annual returns.

Strategy 2: One Day Signal

This strategy uses the previous day's stock movement as the decision maker for whether to take a buy or sell position. The rule is simple – if the price goes down, the next day we sell (or hold, if already in a sell position). If the price goes up, the next day, we buy. By calculating the one-day signal and then shifting it by one row, I was able to incorporate the one-day delay of the trade execution into the strategy performance. The results are below:



Cumulative Return: -61.2%

Sharpe Ratio: -0.0197

This strategy performed very poorly. Not only did it fail to come close to the buy and hold strategy's performance; it lost money overall. The issue here is that the stock market, at the short-term, is volatile. It often will go up one day, then down the next. Tesla especially has frequent spikes and dips, despite its strong upward trend over the 7 years. Since every decision was based on the previous day's stock movement, the strategy failed to capture most stock movements. It was only able to profit or avoid losses when the stock moved in the same direction consecutively.

Strategy 3: Mean Reversion

Mean Reversion describes a phenomenon where, in the stock market, there is cyclical stock price movement around a fundamental trend line. For successful companies, this trend line is a stable upward-sloping line, indicating a mean growth rate over time. Essentially, stocks are always moving above and below their intrinsic value. Sometimes, they move significantly above or below their true value, and the core idea here is that the market will notice this and buy/sell until it has been pushed back to the price that reflects its actual fundamental value. The goal of a mean-reversion trading strategy is to buy when it is undervalued, before it is pushed back to its true value, and sell when it is overvalued.

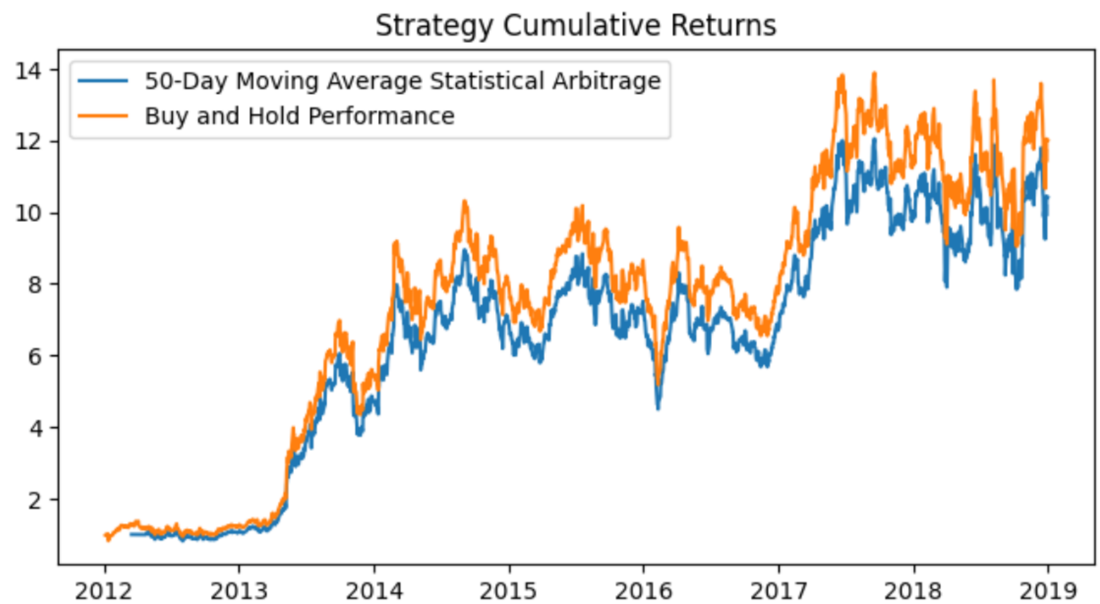
To program this strategy, I used a 50-day rolling window. For each closing price, I calculated the average closing price of the previous 50 days of stock information. I also calculated the standard deviation of those same 50 days. The strategy had different rules for when to buy and when to sell. They are as follows:

$$Buy\ Threshold: Close\ Price < \ 50\ Day\ Moving\ Average - 1.5 * Standard\ Deviation$$

$$Sell\ Threshold: Close\ Price > \ 50\ Day\ Moving\ Average, and$$

$$Close\ Price < 0.98 * Yesterday's\ Close\ Price$$

Essentially, when the closing price drops below 1.5 standard deviations below the 50-day rolling moving average, the strategy takes a buy position. Then, it holds that buy position until the closing price goes above the 50-day moving average (not multiplied by standard deviation) and then drops by 2%. The design of this strategy is intended to ensure the stock is purchased when the stock is likely undervalued, and then doesn't sell until the stock has reverted back to the mean and then dropped 2% in one day. This allows the investor to benefit from the upward movement back to the mean without selling prematurely. The results are as follows:



Cumulative Return: 941.95%

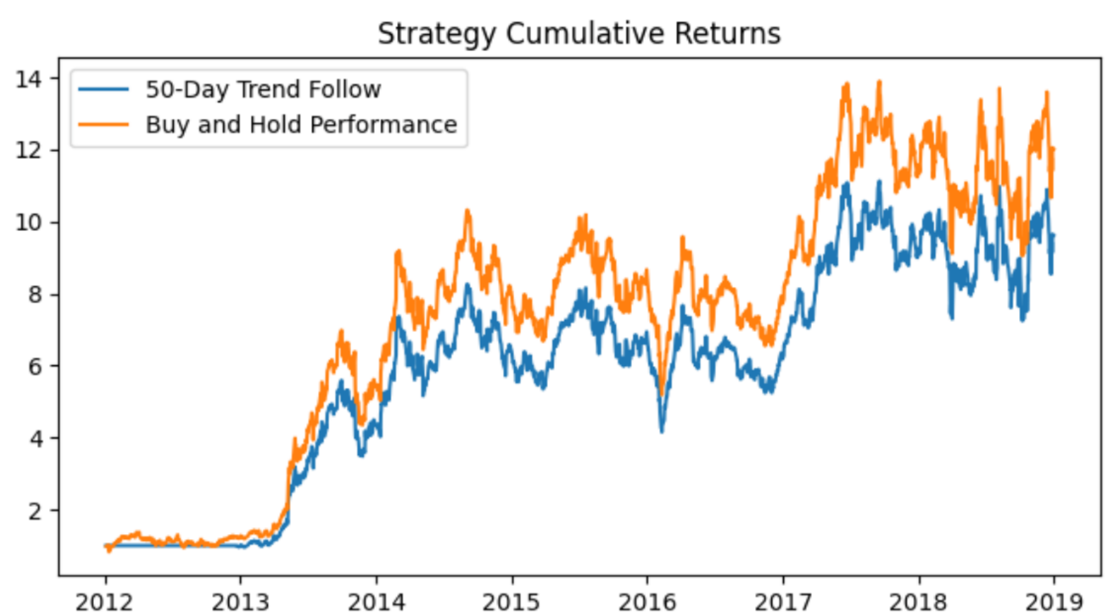
Sharpe Ratio: 0.9464

We see that this strategy performed similarly to the buy and hold strategy. The issue with this strategy is the sell rule rarely executed. What I found through further adjusting of the parameters was that a growth stock like Tesla requires more sensitive sell rules to execute. However, doing this often causes losses, since selling more frequently more often results in lost profits rather than avoided losses.

Strategy 4: Trend Following

With a trend following strategy, we take the opposite approach to mean reversion. Instead of trying to buy when the price is low and sell when the price is high, we aim to buy when the price has recently been higher than the more holistic average, and sell when the opposite is true. More specifically, when the 50-day moving average rises above the 200-day moving average, the algorithm takes a buy position. When the 50-day moving average drops below the 200-day moving average, it sells.

A concern with this strategy is that the algorithm will be always buying right when the 50-day moving average hits the 200-day moving average, and then selling when it drops below; therefore, it may buy and then sell at around the same area of the stock's mean prices, statistically speaking. However, the benefit of this strategy is that when the stock price rises indefinitely, and the 50-day moving average is continuously pulling both moving averages upwards, the algorithm is profiting; and if the opposite happens, and the stock is dropping continuously, a buy position will not trigger until the pattern flips in the bullish direction. The results are below:



Cumulative Earnings: 861.57%

Sharpe Ratio: 0.934

We see another strategy resembling the performance of the buy and hold strategy closely. The conclusion to be made here is that neither of these strategies can effectively trigger sell positions that avoid losses that a buy and hold strategy would incur. Therefore, the delay in buying towards the beginning of the strategy results in lost profits, which means the strategy trails behind the buy and hold performance overall. This is true for **trend following** as well as **mean reversion** in my testing.

Strategy 5: Relative Strength Index (RSI)

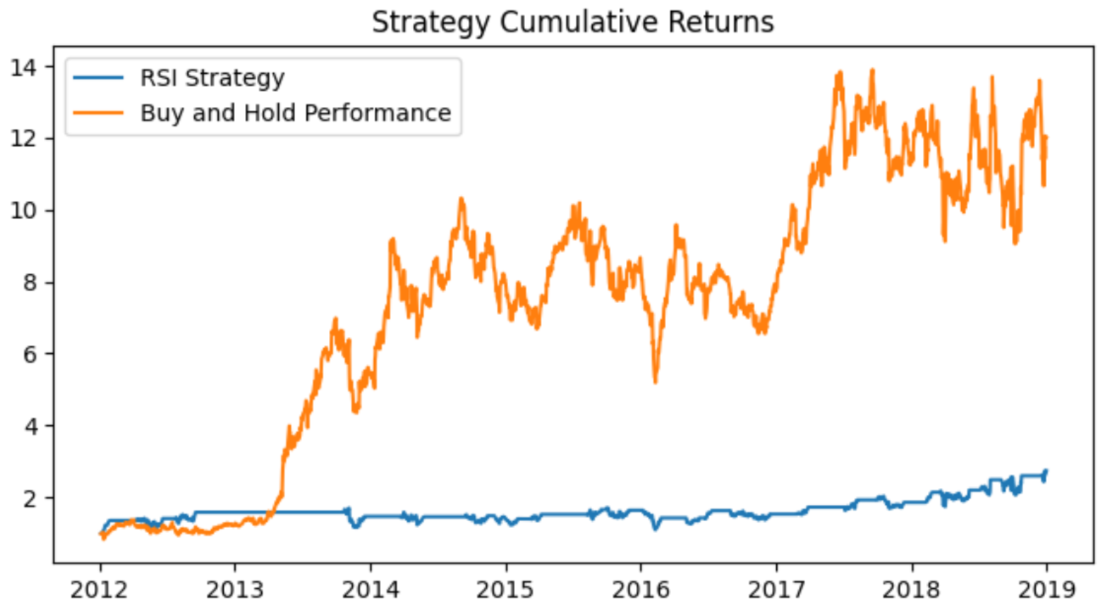
At this point, it seemed that my simpler price-tracking strategies were not giving any benefit over buy-and-hold. I decided to use the Relative Strength Index to try and identify when the stock was overvalued and undervalued. In Zatwarnicki's research about RSI trading strategy, the results showed that "Comparing [RSI] with the traditional buy and hold strategy shows the credible potential of the indicated method" (Zatwarnicki). My results were consistent with Zatwarnicki's, because while the typical RSI range of 30 and 70 proved to be undesirable, I was able to tweak these parameters to achieve improved results.

With an RSI approach, a typical low RSI would be below 30; this means the stock is undervalued. Above 70 indicates overvalued. The issue here is, this is generalized to all stocks; since Tesla is a high-growth stock, the parameters needed to be altered to adjust to its more upward trending price movements. Below are the formulas for how to calculate Relative Strength, as well as its index:

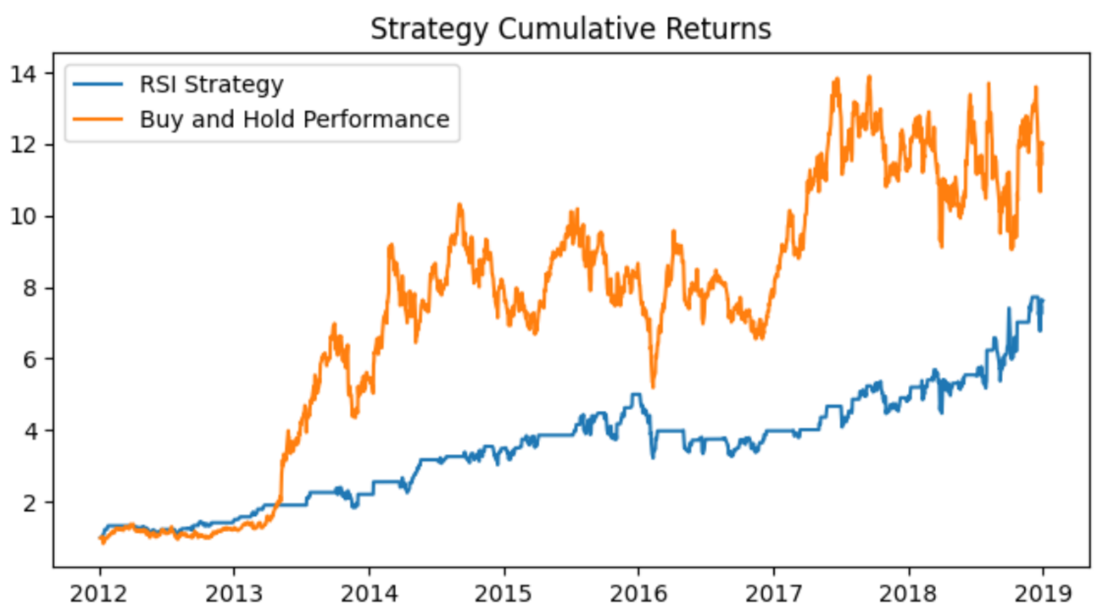
$$RS = \frac{Average\ Gain}{Average\ Loss}$$

$$RSI = 100 - \frac{100}{1 + RS}$$

I first programmed two functions; one would get the RSI value and insert it into a data frame with the closing prices, and the other would apply the strategy described above and calculate the cumulative earnings, with the buy threshold set at 30 and the sell threshold set at 70. The graph for this strategy is below:



It is clear here that the given parameters do not work for Tesla. I decided to bring them closer together, programming the strategy to buy when RSI falls below 40 and sell when it rises above 60. The results improved:



Next, I decided to run every possible combination of buy and sell thresholds and identify the best one in terms of cumulative earnings. By programming two nested loops, I was able to run every RSI buy threshold between 0 and 50, combined with every RSI sell threshold between 50 and 100. The results of this process are below:

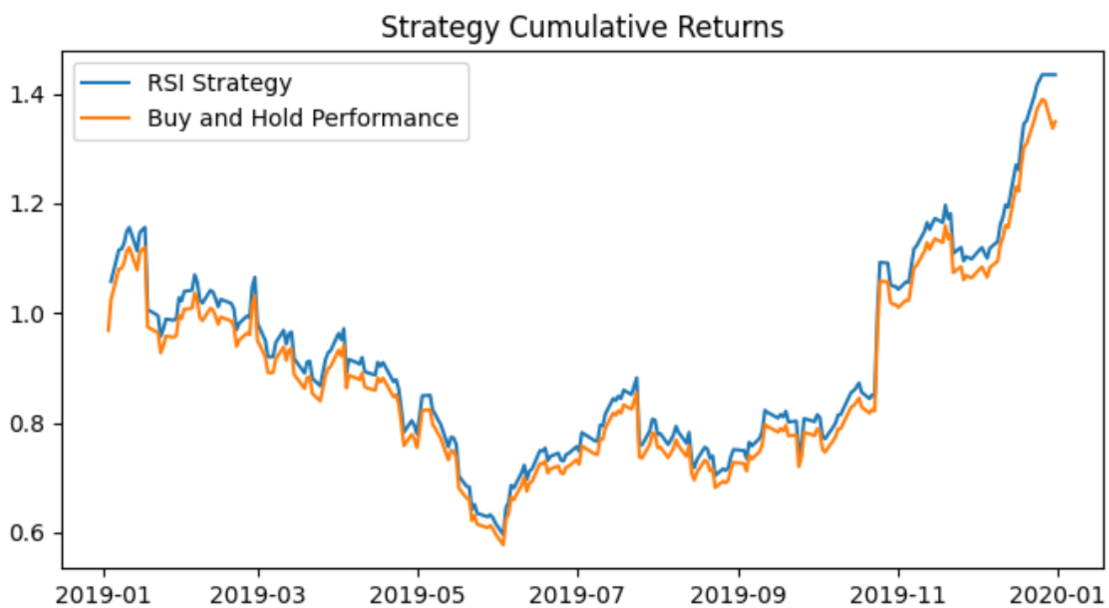
	X	Y	Cumulative_Returns
1470	28.0	92.0	16.346359
1419	27.0	92.0	16.346359
1521	29.0	92.0	16.177738
1827	35.0	92.0	16.177738
1776	34.0	92.0	16.177738

Sorting by cumulative returns shows that the best RSI thresholds to use are 28 and 92. Below is the graph for this strategy with these parameters:

Cumulative Earnings: 1313.01%

Sharpe Ratio: 1.01

Here, we see that the RSI strategy has outperformed the buy and sell strategy in both cumulative returns and in Sharpe Ratio. Since this was heavily trained on the 7-year period, I decided to run the strategy with the same parameters on the holdout set (2019):



Buy and Hold 1 Year Cumulative Earnings: 34.89%

RSI 1 Year Cumulative Earnings: 43.48%

Buy and Hold 1 Year Sharpe Ratio: 0.859

RSI 1 Year Sharpe Ratio: 0.991

As we can see, on the test set, the strategy still outperforms the buy and hold strategy.

Conclusion

What we see in our results is that the Relative Strength Index method shows the greatest results, as it is the only strategy that gets above a 1 Sharpe Ratio. I think the key differentiating factor is that, with the RSI method, I was able to computationally test every possible pair of RSI buy and sell thresholds, which allowed me to use the absolute ideal set of parameters and achieve the best results. I believe doing something like this for the other strategies could improve those methods as well, since optimizing the parameters proved useful for the RSI strategy. As always, overfitting the parameters is still a concern, so testing on future data is an important element.

Overall, we see that calibrating different strategies for a specific stock can achieve better results than a simple buy and hold mode, but I hypothesize that the result of this Tesla stock analysis cannot be assumed to hold true with other stocks. Tesla was a high growth stock from 2012 to 2019, so it's more likely that this RSI-focused strategy would perform similarly on other high-growth stocks. Further research would have to be done on more mature companies to determine the best course of action in those sectors.

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