US Equity Market Intraday Trader Technical Report

Elliot T Jones

April 18, 2024

Abstract

This technical report explores the challenges and outcomes of implementing an intraday "high frequency" trading strategy in the US equity market, focusing on Apple stock. This experiment uses various software to collect market data, design and back-test a trading strategy based on the Relative Strength Index (RSI), and forward-test the strategy. The RSI indicator was chosen for its ability to identify potential trend reversals. Back-testing revealed optimal parameters, including oversold and overbought thresholds and a look-back window of 9 minutes. Forward testing demonstrated a successful strategy, yielding a profit of $13,241.17 over 22 trades. Analysis using statistical tests such as the T-test, Sharpe ratio, and Sortino ratio confirmed the strategy's skill-based profitability and risk-adjusted performance, outperforming both Apple and the S&P500. Insights gained suggest areas for future experimentation, including the addition of multiple indicators. Overall, this report presents a viable intraday trading strategy for Apple stock using the RSI indicator.

1 Introduction

The experiment performed within this report will explore the challenges faced when undertaking the role of an intraday "high frequency" trader in the US equity market. Utilisation of different software, including Trader Workstation (TWS) and Python will be used to collect stock market data, design a back-testing strategy, forward test said strategy, and analyse trading performance. Throughout this report requirements for data collection, technical analysis, and back-testing shall be specified and followed to provide the most accurate and fair experiment. The trader workstation will be used to implement our trading strategy. Allowing us to achieve accurate tracking and analysis for evaluation of our overall performance, such as decomposition of commission costs, comparison to benchmarks and information to perform statistical tests. At the end of the forward testing period justification of the chosen trading strategy will be discussed, highlighting strengths and weaknesses, along with reflection and future insights for if this experiment were to be undertaken again.

2 Collection of data

When intraday trading there are two vital requirements needed, volatility and liquidity. After researching multiple stocks we decided to evaluate Apple for our experiment. This was due to Apple's 5-year monthly Beta of 1.28 and average daily traded volume of 63,159,823. This Beta meant that Apple had slightly more volatility than the market enabling us to see more price fluctuations, but not so much that our profit and loss margins would be uncontrollably risky. Having this volatility provides more chances for our technical indicator's requirements to be met and in turn, enable us to have more trading opportunities. Liquidity is also an important factor as being intraday traders we need to be able to execute trades quickly and at the market price. For example, if we were to trade a stock with a low liquidity like low cap stocks, due to the amount of USD we are trading we would face numerous problems. This includes difficulty in executing orders and large market impact due to a smaller volume of market price orders in the order book, leading to uncertainty of execution price. It is very important for us to avoid illiquid markets as they can drastically affect our profits. We rely on relatively small price movements for profit and if prices are unstable, they will significantly affect this. Using our Python code, we were able to download data from Yahoo Finance, which included the information from each one-minute candle. For example, the open and close price, the high and low price, the volume, and the adjusted close price. We chose a one-minute data frequency as we wanted to have as many trading opportunities as possible in the shortest period and using one-minute data provided us with the greatest chance of this. We chose 20 days of data to download as this would allow us to see the performance of a significant amount of market data in our back-test. This will ensure that we make a reliable, informed choice on our parameters and trading strategy. When calculating our back-testing formulas, we used adjusted close price as opposed to close price. The difference in these prices is that the close price is the raw price, whereas the adjusted close price considers corporate actions such as stock splits, dividends, and rights offerings (1).

3 Technical indicator selection

The technical indicator we decided to trade was the Relative Strength Index (RSI), a reversal based indicator. This means that RSI tells us when the market is going to change direction and signals us to trade for the reversal of a trend. For example, when a stock is falling and has been strongly oversold, we expect the market to switch trends and move upwards and hence we buy, the opposite can be said for when the stock rises. The RSI can be defined as follows,

$$RSI = 100 - \frac{100}{1+RS} = 100 \text{ x } (1 - \frac{1}{1+RS}),\ RS = \frac{\text{Average gain of up periods}}{\text{Average loss of down periods}}$$

To trade the RSI indicator we needed to set our oversold and overbought thresholds and our look-back window. A look-back window is the number of observations used for calculation. For example, since we used a one-minute data frequency a look-back window of 20 would mean that we calculate the RSI based off of the last 20 minutes of data. This meant that when we commenced our forward testing we needed to wait the same amount of time as the look-back window we used in our back-test. It is important we followed the back-test as close as possible as if we didn't, we could experience different results. Our trading strategy was as follows, when the RSI falls past our desired oversold threshold we buy and when the RSI rises past our overbought threshold we will sell. Before we finalised the variables for this trading strategy, we back-tested multiple times with different variables to gain the optimal parameters for our trading strategy.

4 Back-testing

For our back-testing, we used a variety of functions and plots to analyse and select the most efficient variables for our trading strategy. We first visualised the trading volume of Apple (refer to Figure 1) and from this, we observed that the open and close of the market had the most volume traded than at any point in the day. The volume at the start of the day was due to the markets accounting for the news that had accumulated while they were closed. As the markets only trade for 6.5 hours a day, this leaves a lot of time for news to be released when markets are closed. As such, the trading for this news takes place when the markets open, leading to an increased volume of trading than at other periods during the day. At the end of the market day, the volume increases as traders try to avoid large price movements due to any unexpected news that might happen overnight, closing their positions to avoid uncertainty. From this, we will ensure not to trade at the beginning or end of the day, where possible, to avoid this volatility. The plot also shows that Apple stock has lots of liquidity and that we should not experience problems executing big trades. Next, we tested various overbought and oversold thresholds and visualized this on a graph to help us optimize this. First, we tried 20% and 80% for oversold and overbought, respectively; this led to fewer trading indicators and so was not suitable. Next, we tried 40% and 60% thresholds, but this led to the majority of data indicating a trade making the indicator ineffective. Finally, we chose 30% and 70% as our thresholds as these parameters were observed to be the best. From Figure 1, we can see that these thresholds allowed our indicator to hit more frequently but avoid regular market movements as these would make our signal less reliable.

Within our back-test a normal market day contained 390 observations, it should be noted that on some market days we see observations of 388 or 389. This was the case when no market data was recorded for an observation and we filled in this discrepancy using previous observations. First, we back-tested for a look-back window of 20, this achieved a good win-loss ratio of 61.90% but left us with an average of 5.15 trades per day and a total loss of 4.32%, with some days experiencing zero trades. This was not viable, as due to our experiment being over a short period we needed to ensure we could trade every day to fulfil the required 20 round trips. Next, we tested a look-back window of 9 minutes and this achieved significantly better results with an average win-loss ratio of 65.46%, an average of 17.75 trades per day and a total loss of 1.43%. These results were much better, however, our return was still negative. This was to due more impactful losing trades than winning ones, so we chose this as our optimal look-back window. Using the standard deviation and mean return we decided to perform a T-test on these results to see if they were due to skill. From this, we obtained a value of -0.48 which meant that our results were not due to skill and that we could receive different results when we come to analyse our forward testing.

5 Forward testing

During our forward testing, we followed our trading strategy as previously defined but with our optimal parameters obtained from our back-testing. Before we began forward testing it was important to make sure that our RSI indicator on TWS had the same parameters as our back-test. We also ensured to only use market orders while trading to achieve immediate execution, closing all open positions at the end of the day as this was an intraday trading experiment. After familiarising ourselves with the TWS platform we began to trade and during this time made various trades to investigate their market effects, trading over the period from 12/04/24 - 01/05/24. Starting with a capital of $1,000,000 we first investigated the impact of order size varying from order sizes of 200 to 6,000. From a trade size of 200 shares (Order ID - 511080051), we observed that it had the same order and execution price of $168.57, showing no market impact. Whereas a trade of size 5,000 (Order ID - 510574177), had an order price of $166.16 but was executed at an average price of $166.16651, showing a negative market impact. Throughout this experiment we can see that as an order size increases the market impact tends to increase, affecting our execution price. This could be reduced in practice by using a time-weighted average price order, but this is ineffective for intraday trading so we did not use it. From our order size of 5,900 (Order ID – 511095149), we have a positive market impact, meaning our average price was better than when we submitted the order. This was likely due to a big sell order being placed below the market price at the same time as our order. Having a total execution time of 5 seconds, we can see from most of our orders that as order size increases so does execution time, with smaller orders of 200 (Order ID – 511080051), having an execution time of 1 second.

Next, we decided to see the effects of executing a trade through a single exchange, placing an order size of 500 through the New York Stock Exchange (NYSE) (Order ID - 509914322). We saw that even smaller order sizes have a larger negative market impact than the order size of 5,000 seen earlier (Order ID - 510574177), with the order initially being placed at a price of $165.05 but execution at an average of $165.58. This was due to NYSE having a smaller number of orders in the order book compared to the wider market. Since we are only executing through this exchange, we most likely will not be executing at the best possible price, paying a premium reflected in our execution price. This could be utilised if we are trying to avoid an exchange with high commission fees as while forward testing, we experienced that different exchanges tend to have different commission fees. We witnessed that exchanges such as NYSE and PEARL had the same broker execution and regulatory third-party execution fees of $0.5 and $0.153664 per 100 shares, respectively. Whereas some exchanges had less expensive fees such as PEARL and ARCA having regulatory third-party fees of $0.150216 and $0.150224 per 100 shares, respectively. All our trades had the same broker execution fee of $0.5 per 100 shares to open or close positions, as all our orders were through the same broker, Interactive Brokers. We can see that from Order ID - 511140077, we have a commission cost to buy of 0.00295552% and a commission cost to sell of 0.00385222%. This is roughly a similar fee for most of our trades but slightly deviates due to the price of our trades differing, highlighting that selling comes with more commission costs. From a trade with size of 4,000 (Order ID - 512128290), we can see that to open our position we are charged only broker execution commission with a total charge of $20. Whereas when we close this position (Order ID - 512133264), we are charged two commission fees, Broker commission and Third-party regulatory commission, totalling $26.14. These are regulatory fees such as SEC transaction fees and FINRA trading activity fees, these are calculated as 0.000008 * value of aggregate sales and 0.000166 * quantity sold, respectively (2). We can also see from multiple trades that different exchanges have different board lot restrictions, with markets like MEMX executing one lot per trade and NYSE executing 100 at a time. Online brokers allow fractional trading of shares with as low as 0.01 of a share being traded, explaining why we can trade small amounts of Apple without a restriction. We can also observe that bigger exchanges like NYSE compared to IEX and other smaller brokers fill more of our order size, due to the liquidity these brokers hold. We also observed that our market impact in smaller markets was much bigger than that in bigger ones as shown by our execution prices throughout multiple trades.

6 Analysis of results

While trading we slightly deviated from our strategy in some of our trades, purchasing multiple times before selling. This was due to us purchasing multiple times instead of once in a single trade. We still followed the RSI indicator; however, this was not coded like this in our back-test. It could be argued that this did not positively impact our results as 5 of our 6 losses were from these trades. This was due to consistent downward market movements, where the RSI kept going below our oversold threshold. However, the reason we still lost on these positions is because the market rose to the overbought threshold when the price was lower than our average price. We cannot say for certain that these trades produce more losses as our sample size was not big enough to statistically determine this, but we can draw this hypothesis.

The overall performance of this strategy was very good, 22 trades were made with a win rate of 0.72727%, totalling a profit of $13,241.16802 and a return of 2.62%. These values were much better than our back-test as we were expecting an overall loss. We can say from this that our trading strategy was successful in practice. On average our profit per winning trade was $991.39 and the average loss per losing trade was $767.32. We gained an average of $601.87 per trade with an average of 3,444.40 shares for each trade. Our average cost of commission per trade was $51.30 with a total commission of $1,128.50, and out of our Mark-to-market profit, 7.991548489% was taken due to commission. We managed to make an average of 1.83 trades per day, having a total time in the market of 19 hours 15 minutes and 2 seconds. From our back-test, we were expecting multiple trades per day, but this was likely not achieved because we only decided to trade for a short period every day where possible. Our average time per trade was high too, with an average time of 52 minutes and 30 seconds per trade, with one of our trades lasting up to 4 hours 30 minutes and 36 seconds. Although in our back-test we did not experience this, little activity within the market caused this, leading to fewer trading signals. Using the T-test and Sharpe ratio, we tested the null hypothesis that our trading strategy involved no skill and risk-adjusted returns, respectively. The T-test and Sharpe ratio are defined as follows,

$$\text{Sharpe ratio} = \frac{r_A - r_f}{\sigma_A} \qquad \text{T-test} = \frac{\overline{r}}{\frac{s}{\sqrt{n}}}$$

where $\overline{r}$ is the average return, s is the standard deviation, n is the degrees of freedom, r_A is the return of the portfolio, r_f is the risk-free rate (this is 0 as we are intraday trading), and σ_A is the standard deviation of the portfolio. Using these formulas from our results, we receive a T-test of 3.061 at the 99% confidence and Sharpe ratio of 14.70. Our critical value for the 99% confidence interval was 2.518, this meant that we can be 99% confident that our adjusted return was due to skill and not luck. Our Sharpe ratio meant that we had an exceptional return compared to the amount of risk we took on board. Along with this, we decided to compute the Sortino ratio, which is a variation of the Sharpe ratio, using the standard deviation of negative portfolio returns. The Sortino ratio shows our downside risk-adjusted performance of harmful volatility. Our Sortino ratio was 27.33, this suggested that our trading strategy's risk-adjusted performance is superior when considering downside risk as opposed to overall risk. We can see that on the Interactive Brokers' analysis, we have a Sharpe ratio of 10.23 and a Sortino ratio of 28.15. These were different as we had originally made a few trades that were not valid, excluding them in our results. Throughout our experiment, we can see that Apple has a Sharpe and a Sortino ratio of -3.11 and –3.87, respectively and the S&P500 has –5.02 and –5.71, respectively, meaning that our portfolio outperformed Apple and the market benchmark. With Apple and the S&P500 having a mean return of –0.23% and –0.24%, respectively, our trading strategy far exceeded Apple's and the S&P500's risk-adjusted performance and was an excellent strategy in comparison.

7 Conclusion

During this test, we discovered and explored many properties of intraday trading. If we were to conduct this experiment again we would try to stick more closely to the same trading strategy we designed for our back-test. This was much harder to achieve in practice as many factors can affect the way we trade such as behavioural traits and human error. We would also like to test this experiment over a longer period to add more validity to our results as the more trades we make the more reliable our results would be. To further our experiment next time we could try to add multiple indicators to our trading strategy and try to implement them within our back-testing and forward testing as this could provide interesting results. In conclusion, we have successfully produced a skill-based profitable trading strategy for Apple using the RSI indicator, closely following our trading strategy with a few minor mistakes.

8 References and Figures

1. $https : //www.investopedia.com/terms/a/adjusted_closing_price.asp$
2. $https : //www.interactivebrokers.com/en/pricing/commissions - stocks.php?re = amer$

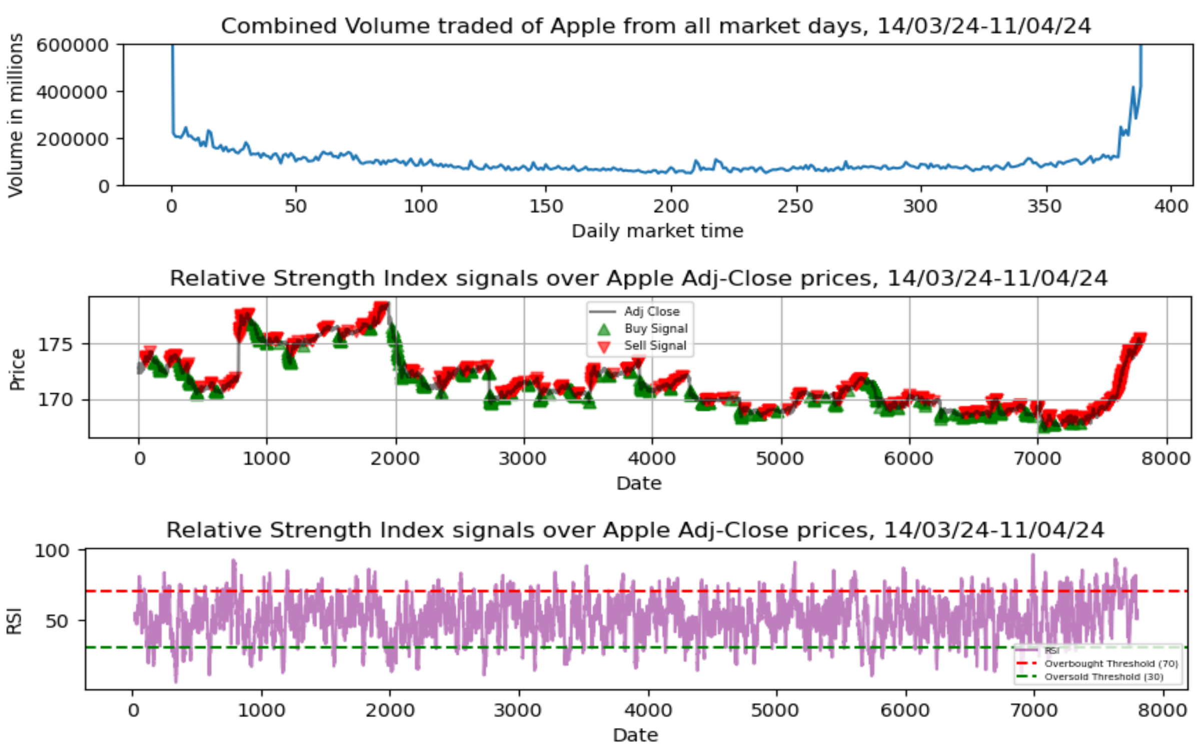

Figure 1: Various Plots