TRADING & QUANTITATIVE RESEARCH REPORT

Momentum Strategy - Events

Investigating intraday momentum effects surrounding interest rate announcements by FOMC

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Introduction & Theory

Introduction

Within finance, in pursuit of greater returns on investments, traders continuously try to design a strategy that would outperform the market. The infamous efficient market hypothesis (EMH) states that "investors should not be able to earn above abnormal returns using public information" and, thus, make it impossible to profit from publicly available historical prices. Despite this, the capital market phenomenon called momentum has proven to reject this hypothesis.

A study performed by Jegadeesh and Titman (1993) showed evidence that abnormally high profits could be yielded by investing in the past top-performing stocks based on three to twelve months historical returns and holding the stocks for the same time frame. Such method of investing is called a momentum strategy and could imply three alternatives: a long position in top-performing stocks, a short position in worse-performing stocks, or a zero-cost portfolio, implementing both long and short positions. In his study, Jegadeesh found that the best strategy was J12/K3 (12 months formation period and 3 months holding period) that would yield on average 1.92% monthly for the period. The strategy excluded the fundamental value of the asset and instead used historical data to observe any trends or patterns and took a position when price momentum was detected. Such findings gave rise to further research investigating different ways to exploit momentum trading strategies in a more recent context [1].

Revised literature has also shown that during the period in proximity to an economic event, the stock market was likely to become more volatile. In some cases, these changes in prices created a strong positive or negative trend, generating a price momentum. Traders exploit such phenomena in their strategies, which have proven to be effective within intraday trading. The general strategy entails that investors detect the movements early, for example, to buy during short-term uptrends and then hold until the stock price loses momentum. A momentum can last a minute, a few hours, or several months. Therefore, it comes with great risk to enter or exit the position too early or too late, causing a substantial loss. For this reason, to produce more legitimate signals of when a buy or sell opportunity is spotted, technical momentum indicators are implemented in the strategy[2].

This project's purpose is to extend already conducted research and analyse short-term momentum effects using technical indicators on intraday data surrounding specific macroeconomic events. As proposed by the collaborating firm LYNX Asset Management, the chosen macroeconomic events are the Federal Reserve (FED) announcements regarding the Federal Open Market Committee (FOMC) meetings' interest rate decisions, which occur eight times per year.

Theory

This report is focusing on how scheduled macroeconomic events, FOMC meeting announcements, can help investors identify opportunities to outperform the market. These events are important as they determine the monetary policy changes, in other words, financial and economic conditions that in turn affect assets prices stability. Historically it has been observed that market activity had been increasing on the days of FOMC announcements compared to other days [2]. Moreover, the FOMC announcements are interesting to research since short-term monetary policy has a great impact on the market.

The FED uses the interest rate to control inflation, for instance, a hike or drop of the interest rate changes the cost of borrowing which will affect investments, savings, and demand, which are some of the crucial factors that drive inflation. Additionally, when a decision is announced, the market reacts immediately, and the reactions depend on the content of the decision, for example, whether it is in line with the market's expectations or not. Overall, it has been observed that whenever there is a change in interest rate, the market becomes more volatile. This is the exact phenomenon this research is intended to examine [2].

When trading in proximity to the events, to be able to maximize the profit, traders frequently use momentum strategies on intraday prices. For investors to be able to forecast these trading opportunities, they apply technical indicators as a part of the strategy. Technical indicators are mathematical calculations based on price, the interest of the asset, and volume. More importantly, technical indicators rely on historical trading data to forecast future short-term price movements [3]. This report aims at researching if there are oddities embedded in the market surrounding these "event days", and in what way, if any, these oddities affect investments. Hence, to limit the sources of error in this research, the investment algorithm implemented to carry out the trading has been designed by combining two commonly used, relatively simple technical indicators: Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI). Another reason underlying this choice of indicators is that the MACD is referred to as one of the best indicators to use along with RSI. The RSI indicator is a momentum oscillator that signals when a price crosses an oversold or overbought region, while the MACD indicator helps investors understand whether the bullish or bearish movement in the price is strengthening or weakening [3]

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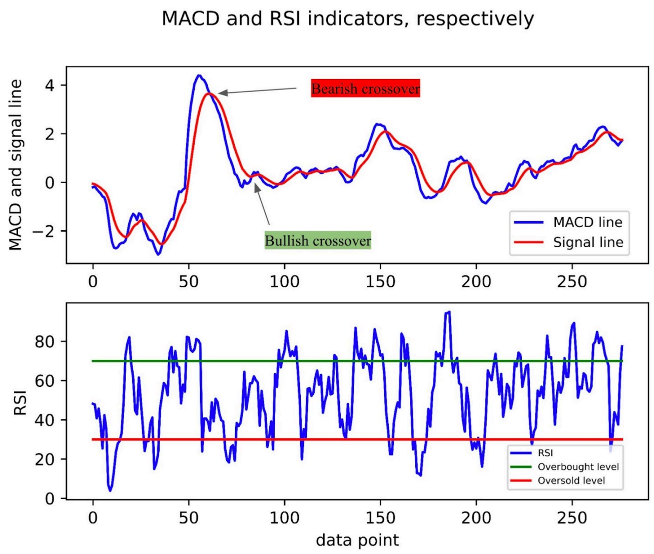

Figure 1*: An example of MACD and RSI indicators*

The MACD indicator consists of the MACD line and Signal line, which are shown in *Figure. 1* The MACD line, displaying the relationship between two moving averages, is calculated by subtracting a longer-period exponential moving average (EMA) of the security's price from a shorter-period EMA:

$$MACD_{cp} = EMA_{12}(cp) - EMA_{26}(cp).$$

Whereas, the signal line, functioning as a trigger for buy and sell signals, is calculated as an EMA of the MACD line:

$$S_{MACD} = EMA_9(MACD).$$

The standardized or default version of settings for the MACD indicator are 12, 26, and 9, meaning that the MACD line is derived by subtracting a 26-period EMA (if the price resolution is 30-minute bars, then a 26-period EMA would include 26 such bars, for example) from a 12-period EMA, and the signal line derived by taking a 9-period EMA of the MACD line. However, as it is later demonstrated in this report, these settings are subject to adjustment depending on the preferences of the investor, asset class, price resolution, etc.

The MACD indicator can be used to generate a variety of trading strategies. Although, one of the most common ways of using MACD is to look for bullish and bearish "signal line crossovers". As depicted in *Fig. 1,* a bullish crossover occurs as the MACD line crosses the signal line in an upwards direction, thus, generating a buy signal. Alternatively, a bearish crossover occurs as the MACD line crosses the signal line in a downwards direction, therefore, creating a sell signal [4].

The RSI, on the other hand, is used to calculate the scale of recent price changes in order to evaluate if the asset is overbought or oversold. As is also depicted in *Figure 1,* the RSI indicator consists of the RSI line, which oscillates between 0 and 100, and two horizontal lines, which indicate overbought and oversold regions. The oscillating RSI line measures the current price strength in relation to a certain period of previous average prices, which are shown in average percentage change, attempting to discover whether the asset is overbought or oversold and thus is likely to revert to normal levels. The overbought area where RSI lies above the overbought level. Contrary, the oversold area is where RSI lies below the oversold level.

The RSI is commonly used with a set of standard input parameters of 14, 70, and 30 and calculated accordingly:

$$RSI = 100 + \frac{100}{1 + \frac{AG_{14}}{AL_{14}}}.$$

Where $AG_{(period)}$ denotes the average gain during the period, and $AL_{(period)}$) denotes the average loss (in absolute values) during the period. The parameters 70 and 30 represent the overbought and the oversold levels, respectively. As with the MACD indicator, these settings are subject to change depending on the preferences of the investor, asset class, data resolution, etc. [5]

Though the signal line crossovers of the MACD in combination with the overbought/oversold levels of the RSI merely generate binary buy and sell signals, volatility measures can be used to indicate the strength of a signal. When entering a trade, the strength of the trend preceding the data point of the signal can be a useful variable to include to make decisions on how much to bet as well as for how long to hold the position (dictated by target profit and trailing stop loss for example, which are explained later on). In this report, the continuous trading indicator Average True Range (ATR) is used for this purpose and is calculated accordingly [6,7]:

$$\min cp = \min(cp_i, cp_{i-1}cp_{i-2}),$$

$$max\ cp = \max(cp_i, cp_{i-1}cp_{i-2}),$$

$$TR_i = \frac{[cp_i - \min cp]}{[\max cp - \min cp]} * 0.5 + 0.5,$$

$$ATR = \frac{1}{n}\sum_{i=1}^{n} TR_i.$$

$$cp_i = i\ th\ \ closing\ price$$

$$cp_{i-1} = (i-1)\ \ closing\ price$$

$$cp_{i-2} = (i-2)\ \ closing\ price$$

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By studying the above formulas, it becomes apparent that ATR is a smoothened average of the previous *n* TRs and belongs to the interval [0.5,1.0], where 0.5 indicates a weak trend, and 1.0 indicates strong trend.

Hypothesis

Our hypothesis assumes that there are differences observed when performing the designed strategy on the historical data of the selected time period. More specifically, it is hypothesized that trades falling under the "event days" category, will show evidence of the positive relationship between the intraday momentum strategy and macroeconomic events, leading to portfolios performing better during days surrounding the events compared to other days.

Data

As previously stated, the research is conducted in collaboration with LYNX Asset Management. Since previous research conventionally claims momentum investing to be significantly more prevalent among equities with high average daily value traded, this study bases its research on data of The Standard and Poor's 500 (S&P500) index. It is important to state that it was decided to proceed with using Contracts for Difference (CFD) closing price data of the S&P500 index, due to restricted access to intraday data provided by other sources. CFD is not the underlying asset, but a tradable contract made to follow the price of the underlying asset, in this case, the S&P500 index. However, the data is considered to be fit for this research as it still provides valuable insights into short-term trading. The time period being analysed ranges from 1/1/2012 to 31/12/2020, while the data used is accessed through Dukascopy and consists of 15-minute intra-daily resolution prices.

Methodology

The investment strategy used in this research generates long and short trading signals when a set of conditions is fulfilled. These conditions are based on the RSI and MACD indicators demonstrated in a previous section. Initially, as a long position was entered, the strategy would be to hold the asset until a sell signal was generated. Conversely, if a short position was entered, it was held until a buy signal was generated. Later it was observed that this strategy did not manage to capture lucrative periods for neutralizing the positions, meaning that positions were simply held for too long, causing a substantial ineffectiveness in the strategy. An example of such trades is displayed in *Figure 2.* Therefore, it was decided to include a target profit level as well as a trailing stop loss to eliminate this issue. A target profit is the price level at which the position is considered to have yielded enough return to be neutralized, deeming the trade successful. The stop loss, in turn, is the price level at which the position should be exited, deeming the trade unsuccessful. At the data point where the position was initially entered, these thresholds are calculated based on the Average True Range (ATR) and logarithmic return.

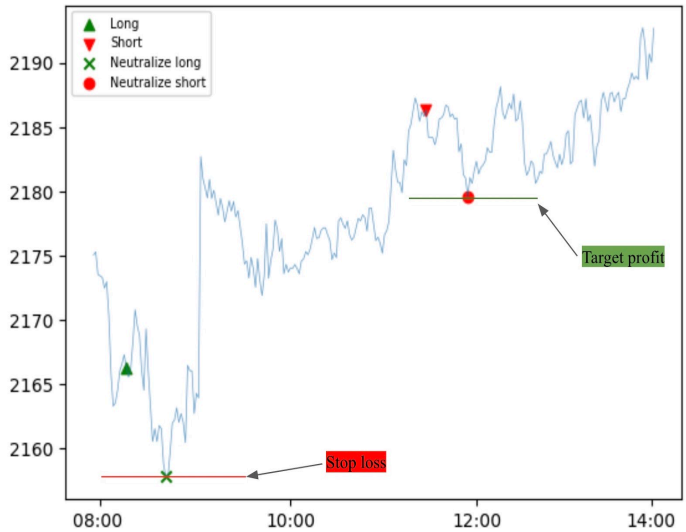

Figure 2: *Illustrative example of an unsuccessful trade where the position was neutralized too early, followed by a profitable trade where target profit was hit right on time (note: y-axis depicts closing price, the x-axis is made up manually for demonstration purposes).*

As it was decided to base this research on 15-min resolution prices of the S&P 500 CFDs, it became apparent that the sensitivity of the indicators used to generate trading signals would have to be adjusted accordingly. After noticing the inadequacy of the default RSI parameters (14,70,30), in the sense that this setting was generating too few signals, and reviewing the literature on intraday trading, it was determined to base the RSI indicator on eight periods instead of fourteen but preserve the overbought and oversold levels. Similar adjustments were made to the MACD indicator, where default settings of (12,26,9) were swapped for (5,40,5), making the indicator significantly faster or more sensitive, thus generating more signals overall. [8] As previously mentioned, the choice of using MACD and RSI and basing the trading conditions on a combination of these indicators to generate signals was made and implemented in the following way:

Long position entered: MACD bullish signal line crossover **AND** RSI below overbought level (70)

Short position entered: MACD bearish signal line crossover **AND** RSI above oversold level (30)

The price to pay for the implementation of multiple indicators was that fewer signals were generated overall, which is quite self-evident as more conditions needed to be fulfilled.

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Method

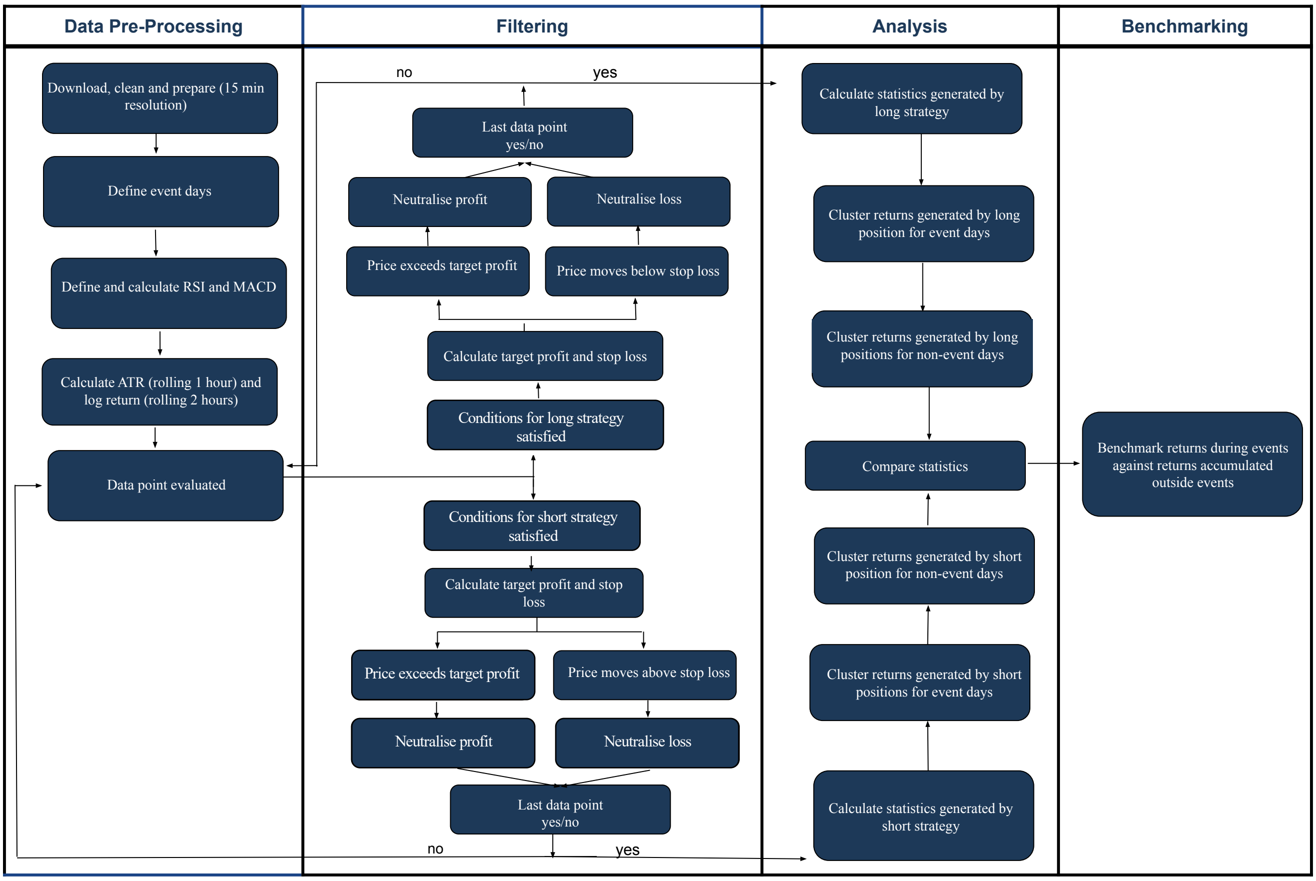

***Figure 3**: Flowchart describing the trading algorithm*

However, by implementing two indicators which are computed based on different types of metrics, where one indicator is used to validate the other indicator's signal, it was believed that such a strategy would provide more legitimate results, as opposed to using the indicators as standalone methods.

When setting the target profit levels and trailing stop loss, it was assumed that there exists a certain correlation between price momentum preceding the point where the trade was entered and how the stock price would continue to increase (decrease for a short position) following the signal. Consequently, the ATR was implemented to adjust these levels, where there would be a 1:1 ratio between the targeted profit and stop loss, meaning that distance to target was equal to the distance to stop loss. Apart from this, ATR was also used to determine how much was bet on any given trade. Since the sample period spanned over nine years (2012-2020), price levels of the CFD would differ significantly over time (first data point collected: $1313.63, last data point collected: $3659.448). This variability in the general price level would come to affect the holding period, as the period depended on the prevailing index price level (greater increase/decrease in price is required at higher price levels for a profit/loss to be achieved than for lower price levels). Hence, to account for this drawback, continuously compounded returns, or log returns, were implemented in combination with the ATR accordingly:

Target profit: ATR (calculated at the data point of the signal, using one-hour historical prices) * logarithmic return (calculated at the data point of the signal, using two hours historical prices)

Stop loss: (-1) * ATR (calculated at the data point of the signal, using one-hour historical prices) * logarithmic return (calculated at the data point of the signal, using two hours historical prices)

Analogously, to measure the stock price development following a signal and keep track of when target profit/stop-loss levels were breached, logarithmic returns were applied in this case as well. The entire method used in this research is depicted in *Figure 3*. Apart from this, it was assumed that it was possible to acquire or short a certain proportion of a share as a position was entered. Hence, the ATR was also used to determine what proportion was bet on any given trade (as ATR ranges between 0.5 to 1.0, smallest bet was half a share, largest bet was one share).

As the strategy was set, the benchmarking was conducted with the sole purpose of comparing how the algorithm performed during events to how it performed overall. To categorize event days and non-event days, data from U.S. Federal Reserve was extracted and

Result & Analysis

a date was classified as an event day if it occurred on:

- One business day prior to the event, or;
- The day of the event, or;
- One business day post the event.

If one of the previously stated days fell on the weekend, then only the surrounding workdays would be categorised as "event" days. For example, in case the event day falls on Saturday, Friday and the following Monday would be classified as "event" days.

The trading strategy was scripted and implemented in Python, utilizing the Pandas and NumPy libraries primarily (additional libraries were used for visualization purposes).

Result and Analysis

A notable observation that could be made before analysing the obtained results was that the CFD data sample of the period 2012/01/19 to 2020/12/01 had risen from $1313.63 to $3659.45. Therefore, if a long position was entered at the start and neutralized at the end of the period, the investment would have yielded a return of 178.58%. Based on this observation, one could expect the long strategy of the research to outperform the short strategy during this period, especially as the algorithm conditions used to implement the strategies were inverses of each other.

In 2020, the global pandemic had substantial adverse effects on economic growth, sending the equity markets such as S&P 500 into a tailspin. By March 23, 2020, the index had plummeted from 3,386.15 to 2,237.40, recording more than a nearly 34% decrease over just one month. This could explain the spike in cumulative short returns observed in 2020 in *Figure 5* as the S&P 500 index fell into the bear market [9].

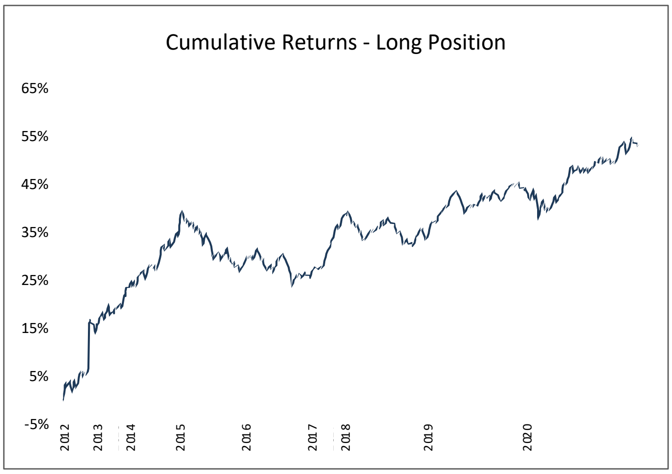

***Figure 4**: Cumulative returns of the long position*

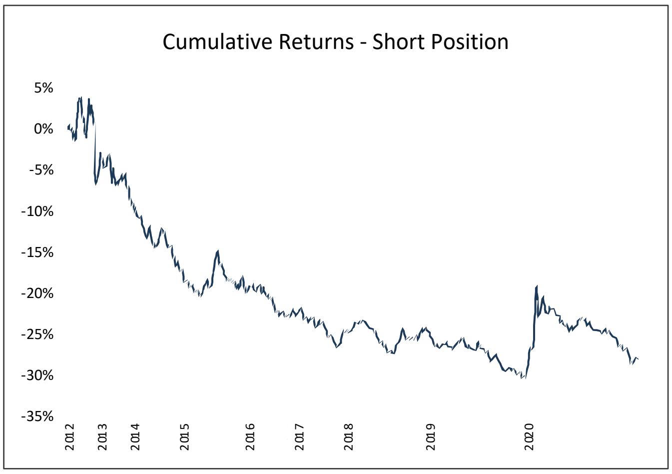

***Figure 5**: Cumulative returns of the short position*

	Overall		During Events	
	Long p.	**Short p.**	**Long p.**	**Short p.**
Average Return	0.1%	-0.0068%	-0.0016%	-0.0086%
Total Cumulative Return	53.87%	-27.99%	-0.1956%	-0.3271%
Win Rate	53.0%	47.4%	50.0%	48.1%
Total Trades	4458	4659	444	445
Av. Hold Period (15 min bars)	18.14	17.95	15.86	15.27
St.D	0.2503%	0.2345%	0.2170%	0.2084%
25th Percentile Return	-0.1648%	-0.1582%	-0.1739%	-0.1736%
50th Percentile Return	0.0765%	-0.0651%	-0.0052%	-0.0719%
75 Percentile Return	0.1706%	0.1519%	0.1695%	0.1513%
Long Short Ratio*	0.957	0.957	0.976	0.976

***Figure 6**: General Statistics*
**number of long trades / number of short trades*

	Overall	During events
Skew long returns	-0.797	0.05
Skew short returns	0.746	0.911

***Figure 7**: Pearson's coefficient of skewness*

Result & Analysis

As suspected, the long strategy displayed in *Figure 4* outperformed the short strategy depicted in *Figure 5* - entering a long position during the sample period would on average yield a negligible positive return of 0.0001 percent while a short position on average ended up yielding a negative return. However, with this background, an interesting observation to highlight is the relatively similar win rates of the two strategies. As displayed on *Figure 6,* out of 4,458 long trades, the algorithm was successful in predicting 2,362 of them (53%) correctly, meaning that the closing price during the period following the signal exceeded the targeted profit level calculated at the data point where the position was entered for these trades. While it is possible to distinguish a certain positive relationship between returns and win rate for long positions, the statistics of the short positions do not follow the same pattern. We observed a relatively high win rate of 47.4% (considering the long-term market trend), but using the graph of cumulative returns as a reference, it suggested that the loss-making trades were worse than the profitable trades were good (otherwise, as the win rate is approx. 50%, returns would be reverting to 0 overtime).

While looking at the results generated overall as compared to results generated only based on data points during events, we were able to discover some interesting features in the data. Contrary to what was predicted in the hypothesis of the project, both long and short portfolios were on average performing worse during events than overall. Notable is how the win ratios of the portfolios during events were still similar to those overall. The median return (50th percentile) for both long and short positions during events was lower than the median for the positions overall. This was also reflected in the skewness calculated for the different sets of returns presented in *Figure 7*. The skewness for long returns overall was found to be -0.797, suggesting more weight in the right tail of the distribution. Opposed, the skewness for long returns isolated to events was 0.05, indicating more weight in the left tail of the distribution. The same pattern was found for short returns overall and during events. By this observation, it became apparent that returns generated by the algorithm, for both long and short positions, were affected negatively by the market conditions during event days.

However, the total amount of trades distributed between long and short positions were relatively similar for event days and overall, suggesting that the relative frequency at which conditions were fulfilled for each strategy was not affected by events.

A first look at the results revealed a pronounced difference between returns occurring during events compared to returns overall. However, there was a valuable information not yet unveiled, which could help to better understand why these dissimilarities were present. To visualize the returns and efficiently compare those generated during events to those generated overall, histograms have been used. From the results obtained in the previous section, we were expecting to observe a greater distinction between events and overall for long positions than for short positions.

As is depicted in *Figure 8*, there was a notable difference between long returns during events and long returns overall. Given the vast difference in sample size between event days and non-event days (444 trades during events, 4,458 trades overall) and for comparison, an additional plot *(Figure 9*) containing the same data was produced, but categories were normalized independently which eliminated the bias generated by the difference in sample size. Although the graphs appeared relatively similar, they were distinguishable from each other where returns generated during events were more prevalent to assume a negative value, and returns overall were more likely to be positive.

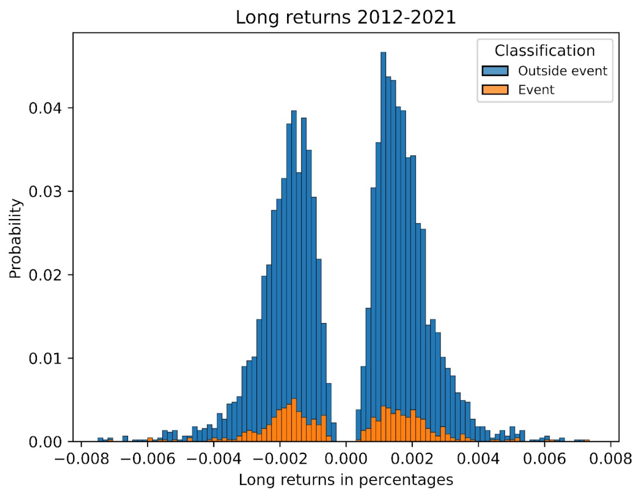

Figure 8*: Long returns distribution*

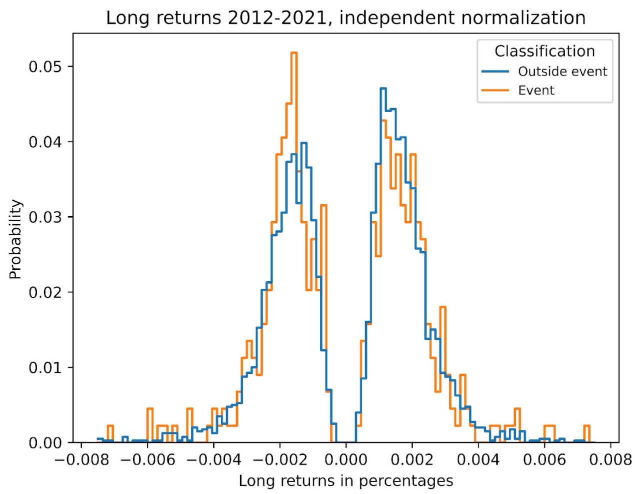

Figure 9*: Distribution of normalized long returns*

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Analysis & Conclusion

However, to be able to make this claim with certainty, a statistical t-test was performed with the null hypothesis: the mean of the long returns overall is significantly different from the mean of returns generated during events. The p-value observed after performing the test showed to be 0.20 (p-value < 0.05 needed for statistical significance), which was not enough evidence to reject the null hypothesis and claim that the means of the different categories are significantly different.

The same pattern was not as evident in the histograms for short returns (*Figure 12 & 13*), where the plot of independently normalized returns could suggest the relationship to be reversed. However, the difference in average return for short positions during events and overall was not as distinct as in the case for long positions, and more data would need to be examined to conclude this point. As could have been expected, the t-test did not generate a low enough p-value for the null hypothesis to be rejected in this case either.

Furthermore, an interesting observation could be made when comparing the tails of the distributions. For both long and short returns during events, the distribution was shaped with a thicker tail compared to the distributions of the returns overall. This indicated that abnormal returns, in either direction, were more likely to occur during events than outside. Even though the strategy constructed in this research did not manage to capture this favourably, it suggested that there was an opportunity to capitalize on the peculiar market conditions surrounding these events.

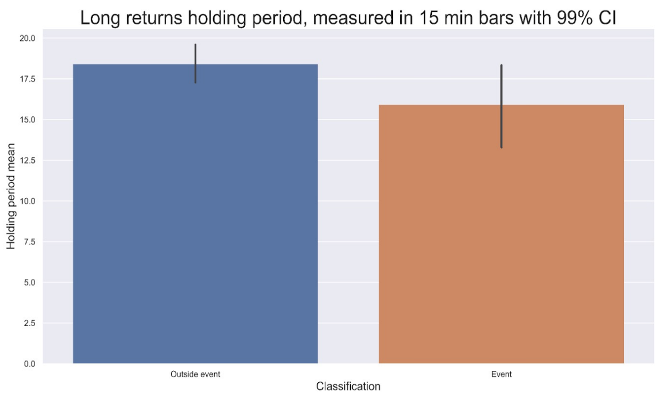

***Figure 10**: Long position holding period. The height of the bar corresponds to the mean for each category, and 99% of observations are contained within the centred stripe.*

Although we were not able to statistically reject the null hypothesis for either long or short position returns, the results were promising and could be investigated further. A measurement that characterizes the trade is the length during which the position was held. A shorter holding period would indicate that the price succeeding the signal develops, in either direction, more rapidly. Hence it was desirable to analyse this metric and compare it between days falling outside events with days during events. As is depicted in *Figure 10,* long positions during events were neutralized faster than long positions outside of events. As the figure suggests, it was even clear that the 99th percentile of the long positions during events was closed faster than the pace at which the long positions outside of events were closed on average. Similar results were obtained when plotting short positions holding period (see appendix). This was an indication that the market was more volatile during events and provided a good reason to re-assess the investment strategy when such a period was approaching, even though this research had not been able to provide enough support to point out how such a re-assessment ought to be carried out.

Conclusion

The overall results compared with the ones from the event days show that both the long and short strategies performed worse during days that fell under events. The win ratios between trades entered overall and during event days were similar; however, higher average returns for the overall trades were observed compared to the event days. To investigate the significance of the mean return difference between the returns overall and during event days, a statistical t-test was performed. The test did not show any evidence that the returns of the different samples were significantly different. Additionally, distribution of the long and short trades for these two categories were also relatively similar, which indicated that the relative frequency of which the conditions were fulfilled for each strategy was not affected by the events. The positions were neutralized faster on average during event days than overall, which suggested that the market is more volatile during event days than on other days.

The increased volatility during the event days was in line with the expectations based on the theory. However, as suggested by the content of the previous paragraph, the hypothesis that the portfolios would perform better during events compared to their performances overall could not be proved to hold true. Several factors could be addressed as possible explanations for this outcome, where the investment strategy would be one of them. It became apparent from the results obtained that the investment strategy did not manage to capture the peculiar market conditions during events.

Conclusion

Nevertheless, the strategy is ought to be analysed further and adjusted accordingly in order to successfully take advantage of Federal Reserve interest rate announcements and their impact on the market. Also, in order to rule out the randomness in the market to a higher degree, more testing on historical data should be conducted. Possibly, including a larger sample size could prove the statistical significance of the t-test performed in the analysis.

If a successful trading strategy is to be designed, it is also desirable to further analyse the extent of the period during which the strategy is deployed. Due to the limitations of the report, the classification of "event days" was not based on any involved analysis. Perhaps, returns could be additionally boosted by dissecting the days and choosing the optimal time period surrounding these events.

Lastly, it is important to note that this research has excluded the impact of transaction costs, which historically has had a significant impact on performances of strategies deployed in live trading, especially strategies focusing on short-term trading. If the transaction fees were accounted for, all the calculated returns would be significantly lower as the highest average return observed was approximately one percent.

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Appendix

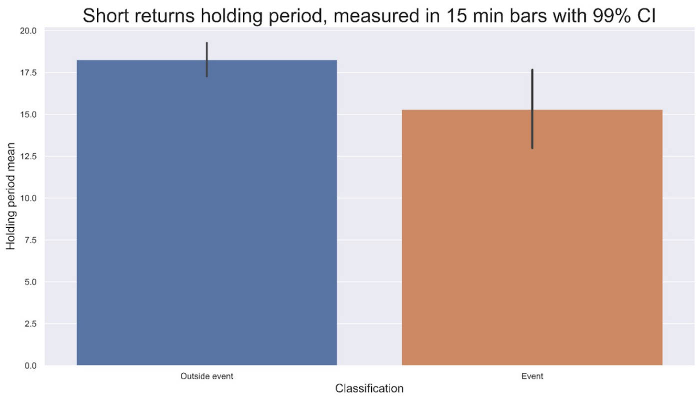

***Figure 11**: Short position holding period*

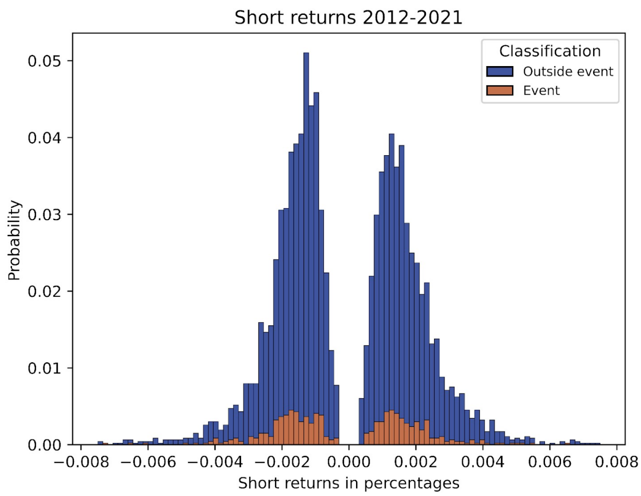

***Figure 12**: Short return distribution*

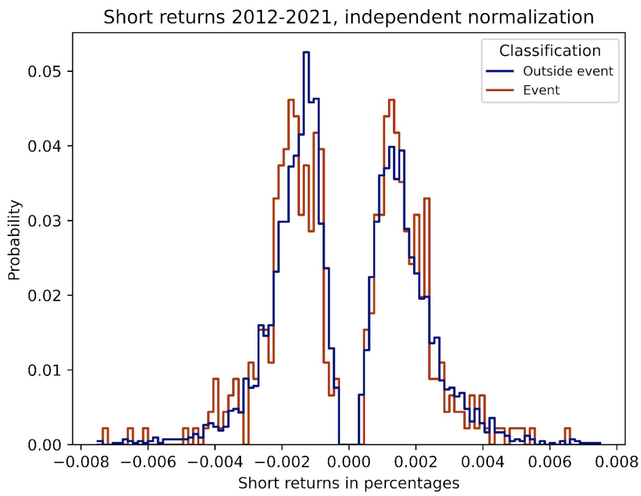

***Figure 13**: Distribution of normalized short returns*

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