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Master Thesis

Backtesting of Trading Strategies for Bitcoin

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Abstract

Bitcoin's (BTC) popularity has risen massively over the last few years. One reason is a growing fascination in the cryptocurrency's decentralized nature and the revolutionary blockchain technology behind it. The other key reason is the meteoric rise in price since Bitcoin's inception in 2008. Characteristic are the many rapid and parabolic price rises followed by a burst of the bubble.

According to several recent studies the Bitcoin market is still young and inefficient [12, 14]. In order to verify the claim and motivated by potentially large returns of such a new market we tried to find a trading strategy with an as high as possible risk-adjusted return. The aim was to capture the gains of Bitcoin's price rise, but not to suffer the massive drawdowns when it crashes. More specifically, the goal was to find an algorithmic long-short trading strategy on the hourly BTC/USD chart with an as high as possible Sharpe ratio, which is a measure for risk-adjusted return. Methods used were combinations of some of the most popular technical indicators such as MACD, Bollinger Bands and moving averages. During the thesis a handy indicator was developed, which enables to classify Bitcoin's price action into different volatility regimes. It was named the volatility-level-indicator, or short VLI.

The final long-short trading strategy of the thesis uses a combination of the Bollinger Band indicator, volume and different moving averages as confirmation signals. A backtest from June 1st 2013 until March 1st 2019 showed that the strategy improved the Sharpe ratio from a value of about 1.1 by simple buy & hold to 3.2. Also, the maximum drawdown was reduced to 25% compared to 85% of the benchmark. These promising statistics are in accordance to the mentioned studies and show how inefficient and immature the Bitcoin market still is.

Contents

1 Introduction

1.1 What is Bitcoin?

Bitcoin (BTC) is considered the first digital currency that is completely decentralized. Since there is no single entity or institution that governs over Bitcoin, it is censorship-resistant and permissionless [1]. Bitcoin's history dates back to 2008, where a person or group called Satoshi Nakamoto posted a paper called ”Bitcoin - A Peer to Peer Electronic Cash System” in a cryptography mailing list. In this paper Satoshi Nakamoto describes Bitcoin as ”an electronic payment system based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party” [2]. To this day Satoshi's real identity remains unknown.
The open-source Bitcoin software was released in January 2009 and with it mining - a process through which new Bitcoins are created and transactions are validated and recorded on the blockchain - started. Blockchain is the new technology underlying Bitcoin, which acts as a system of transaction bookkeeping [3, 4]. At the time of writing 1800 Bitcoins get generated per day. Satoshi Nakamoto's porotocol introduced digital scarcity by cutting this mining reward in half every four years until a maximum supply of 21 million Bitcoins will be reached. So far on May 30, 17 730 300 Bitcoins have been mined and only around 15 percent more are left to be acquired by miners. The next Bitcoin halving occures in less than one year on approximately May 22, 2020. Because of Bitcoin's scarcity it is often referred to as digital gold [5, 6].
Andreas Antonopoulos, one of the most recognized experts in cryptocurrency believes that Bitcoin could not just be used as a global currency and store of value such as gold, but as the ground layer of a new kind of internet: “This is the the internet of money; it's not just money for the internet. [. . .] The bitcoin currency is just the first application – it's like email on the internet – it's good enough to change the world and have everyone adopt the internet. . . ” [7]. Hopeful of a censorship resistant, permissionless currency that has the potential to disrupt gold as a store of value and be the basis of a new ”internet of money”, the Bitcoin price speculation started.
In the beginning of 2011 one could buy one Bitcoin for \$0.30. Only half a year later, in July 2011 the Bitoin price was already over \$15 and at the end of the year it came crashing back down to \$3 [8]. Figure 1 shows the BTC/USD chart from 2012 to 2019 and illustrates Bitcoin's meteoric rise, hitting \$1000 for the first time in 2014. Most people have heard about Bitcoin during the

last bull run, which catapulted Bitcoin from around $250 in late 2015 up to its all-time high of almost $20 000 in December 2017. At the peak, Bitcoin's market capitalization was over 330 billion [9].

Figure 1: Bitcoin's historical price chart from 2012 to early 2019 showing logarithmic price on the left axis. The drawdown is visible as a light blue area in the background with the corresponding scale on the right vertical axis. Of notice is the tremendous growth in Bitcoin's price, as well as several drawdowns of over 30%. Two major drawdowns of over 80% can be seen during 2015 and 2019.

Figure 1 does not only show the exponential growth in Bitcoin's price, but also the volatility and many large drawdowns of over 30% which investors had to stomach over the years. Some drawdowns, as can be seen in 2015 and 2019 were even over 80%. These numbers illustrate how risky it is to buy and hold Bitcoin. Sure, if Bitcoin becomes the new digital gold and its market capitalisation rises to golds current market capitalisation of $6 trillion, then there is still much more room for price discovery [10]. However, since Bitcoin increased so quickly in popularity, hundreds of alternative cryptocurrencies using similar blockchain technology emerged. Litecoin and Ethereum are two examples. It is my personal belief that Bitcoin will remain the market leader for many years to come because of its head start, security and decentralization of the network. However, Bitcoin could also end up as the Napster of digital currencies as Brad Garlinghouse, the chief executive of the rival cryptocurrency Ripple believes [11].

1.2 Motivation for a Trading Strategy

Related Work The work "An Agent-Based Artificial Market Model for Studying the Bitcoin Trading" by Luisanna Cocco *et al.* studied the BTC/USD market by means of an agent based model [12]. Contrary to efficient market hypothesis their findings have shown that it is possible to predict Bitcoin market movements by analyzing historic price action. Efficient market hypothesis (EMH) states that the price of an asset fully reflects all available information about its value [13]. Therefore it would be impossible to trade an asset, in our case Bitcoin, by using historical data and beat the market. In the paper of Luisanna Cocco *et al.* two kinds of agents were modeled, Chartists and Random traders. The Chartists that traded according to the trading system with the best sets of rules were found to generate the highest profits in training and testing periods [12]. Another related work is "Application of Machine Learning Algorithms for Bitcoin Automated Trading" by Kamil Żbikowski. Technical analysis methods were combined with complex machine learning models. Similarly to Luisanna Cocco *et al.* it was found that the performance of the tested algorithms was promising and the compound return over the backtested period would exceed reasonable levels knorn from financial markets [14].

Goal of the Thesis In order to verify the results from the presented works above, which showed that the Bitcoin market was still inefficient, a trading strategy was designed. A quantity called the "Sharpe ratio", developed by Nobel laureate William F. can be used to compare the return of an investment strategy to its risk. The higher the Sharpe ratio, the higher the risk-adjusted return and therefore the better and safer the trading strategy [16]. If it was possible to develop a trading strategy with a higher risk-adjusted return than the benchmark - in our case Bitcoin - it would confirm the hypothesis. Bitcoin is such a volatile asset that it often seems as if one day of Bitcoin trading is like one week in traditional markets. Also, Bitcoin does not have the traditional trading hours and is traded 24/7 every single day of the year. This thesis therefore focused on the development of a trading strategy on a relatively short time interval chart, more specifically the hourly Bitcoin chart. Aim was to find an algorithmic long-short trading strategy, which would try to capture most of Bitcoin's upward movement, but severely reduce the volatility and also the drawdowns. Finding a trading strategy on the Bitcoin hourly chart with an as high as possible Sharpe ratio therefore summerizes the goal of the following chapters.

1.3 Technical Analysis

Holding Bitcoin through its ups and downs can be nerve-wracking since it is such a volatile asset with historically many drawdowns. In such a market, it is easy to get emotional over big gains or losses in a short amount of time, which makes the decision-making process of buying and selling hard. From an investment perspective Bitcoin is therefore very speculative and one could possibly lose all the invested money. There are other ways to navigate through the Bitcoin market and profit from its price growth that can be less risky. One can define a clear set of rules - a trading strategy - in order to trade the market in a totally unemotional way. The algorithm defined by those rules can then be programmed into a computer that automatically generates the ”buy and ”sell” signals [15]. The method to find low-risk entry and rational exit signals in a market is called technical analysis. John J. Murphy, who is considered the father of intermarket technical analysis, defined technical analysis as ”the study of market action, primarily through the use of charts, for the purpose of forecasting future price trends”[15]. The other approach to trade a market is fundamental analysis, which attempts to evaluate the intrinsic value of an asset. Technicians would say that the technical approach includes the fundamentals. That is, because one can argue that anything affecting price, such as fundamentals, politics or psychology are actually already priced in the market. Bitcoin is a relatively new and volatile asset that is susceptible to all kinds of news, which makes price easily manipulable. The technical approach seems a reasonable way to trade the Bitcoin market, because it blocks out a lot of the noise by only focusing on the chart and some supporting technical indicators [15]. Such indicators are mathematical constructs derived from price or volume. A few of them are explained in the next section.

1.3.1 Technical Indicators

In the following, some of the most used technical indicators are presented. These were also the indicators that were used to develop the trading strategy in this thesis.

- Simple Moving Average (**SMA**): The SMA is defined as the arithmetic mean of an asset’s closing price over a certain period. It is one of the most used technical indicators. The larger the period, the slower it reacts to changes in price [17].

- Exponential Moving Average (**EMA**): A special kind of moving average that places more weight on the most recent closing prices. See Investopedia for the exact definition [18].

- Moving Average Convergence/Divergence (**MACD**): The MACD- indicator was developed in 1979 by Gerald Appel. It is calculated by subtracting a short period (standard: 12) EMA from a longer period (standard: 26) EMA. On top of the MACD-line an extra nine-day EMA called the "signal line" can be plotted [19]. Figure 2 shows a visualization of the MACD for a better understanding.

Figure 2: MACD – BTC/USD hourly candle chart with the MACD indicator below. The MACD line in Blue can be seen, which is calculated by subtraction of the two black exponential moving averages in the chart with standard periods 12 and 26. A crossover of the MACD with the signal line (orange line) or the base line can be interpreted as a trading signal.

- Bollinger Band (**BB**): The Bollinger Band was developed by John Bollinger in the 1980s. Three lines compose the Bollinger Band: A SMA with standard period 20 of the closing prices (middle band), an upper and a lower band. The upper and lower bands are typically two times the 20-period standard deviations above/below the middle band. Since the standard deviation is a measure of volatility, the distance between the lower and upper bollinger bands becomes wider the more volatile an asset is [20].

- Bollinger Band Width (**BBW**): John Bollinger defined the BBW- indicator as the width between upper and lower Bollinger band normalized by the middle band as in (1) [21]. Figure 3 shows how the BBW reacts to different levels of volatility in price. If there is little price action, the BBW squeezes and a breakout either up or down can be expected.

$$\text{BBW} = \frac{\text{upper band} - \text{lower band}}{\text{middle band}} \tag{1}$$

Figure 3: Bollinger Band & Bollinger Band Width (BBW) – Same chart as in Figure 2, but this time with the standard Bollinger Band indicator in the price chart and the Bollinger Band Width below. When price action becomes more volatile, the difference between the top- and bottom-band widens, which is reflected in the BBW indicator. A crossover of a price-candle with one of the Bollinger Bands can be interpreted as a trading signal.

- Volume (**vol**): Volume is defined as the number of shares - or in our case the number of Bitcoins - that have been traded over a certain amount of time. Volume is highly correlated to volatility and therefore also to the Bollinger Band Width. Both indicators, volume and BBW, can be used as a way to confirm the strength of price movement. Volume is not to be confused with liquidity, which is a measure of how easily a market price of an asset can be changed [15, 22, 23].

- Highest High & Lowest Low (**HH** & **LL**): Two technical indicators that simply do what they say: plot the highest and lowest price over a certain period inside the candle chart, forming a price channel [25]. Figure 4 illustrates this nicely, where the green line shows the Highest High of the last twenty candles and the red line the Lowest Low.

Figure 4: Highest High (HH) & Lowest Low (LL) – Same chart as in Figure 2, but with the HH and LL indicators. A crossover of a price-candle above the green HH-line could signal a long-trade entry. On the other hand, a short-trade could be triggered when price crosses down the red LL-line.

1.3.2 Trading Strategies

By use of one or several of the above indicators, one can define a set of rules - a trading strategy - that specifies when to buy or sell in a market. Some examples of such trade-entry and trade-exit signals are listed below.

- Moving Average Crossover: Price crossing over or under a moving average can be used as a simple entry or exit signal. A faster MA crossing up a slower MA is often used as a long-signal [24].
- MACD Crossovers: Both, the cross-overs/unders of the MACD with the signal line or the base line can be interpreted as buy/sell signals. The crossover with the base line would be the same signal as the crossover of the 12-period EMA with the 26-period EMA.
- Price Channel Break: A buy signal could be triggered when price leaves the HH-line of the price channel. Similarly, a spike below the

LL-line could trigger a sell-signal. One can decide if the candle leaving the channel has to close outside of it in order to trigger a signal.

- Bollinger Band: About 90% of the time, price fluctuates between the upper and lower Bollinger bands. So any time price breaks above or below the band marks a special event. As an example, one could use a break above the upper Bollinger band as buy signal, or the cross-down of price below the lower band as a sell signal. The strategy in this paper actually uses the cross-down of price with the upper band as a long signal [20].

1.4 Backtesting from a Physicist's Perspective

Friends at the department of physics might read the thesis and ask how backtesting of trading strategies has any relation to physics. Wei-Xing Zhou *et al.* have proposed and explained in their paper that the properties of returns obtained by a trading strategy provide a kind of "spectroscopy" of the prices. Thus, a trading strategy can be interpreted as a nonlinear transform allowing one to analyse the input price time series, as well as other input information like volume [26].

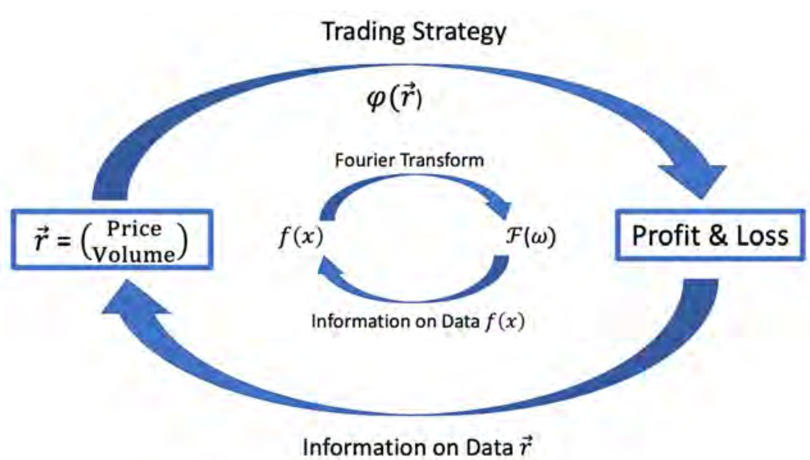


Figure 5: Illustration of how both, the Fourier transform and also a trading strategy can provide more information about the actual data. This cycle of attaining more information about the data by analyzing the statistics of a strategy and then trying to improve it, was repeated many times in order to find a good trading strategy.

Figure 5 above clarifies in a more visual way the analogy between a trading strategy and spectroscopy, specifically Fourier-spectroscopy. Fourier-spectroscopy is a way to gain information about a light source - or other forms of radiative sources - by Fourier-transforming an interferogram. An interferogram is the "raw data", which can be attained by use of an interferometer. Fourier-transformation maps the data to the frequency space, which gives the spectrum of the light source [27]. Similarly, price and volume are the raw data while backtesting a trading strategy. Figure 5 illustrates how the strategy transforms the data into a new space, where profits, losses and other statistics of the trading-strategy can be analyzed. Those statistics can again - in analogy to Fourier-spectroscopy - provide valuable information about price action of the data. The way of finding a Bitcoin trading strategy in this paper, was to repeat this cycle many times.

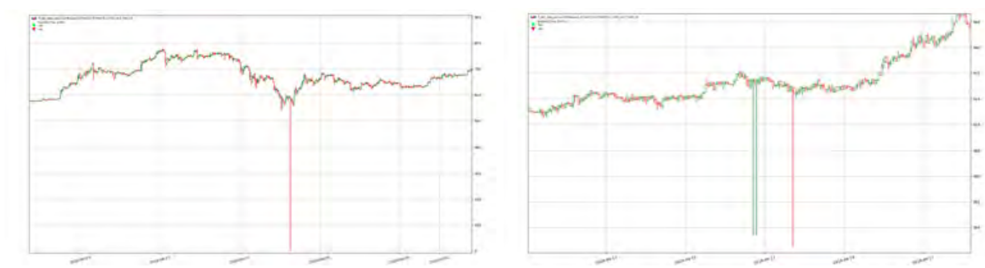
2 Methodology

2.1 Data

The analysis was performed on BTC/USD hourly OHLCV data (O: Open, H: High, C: Close, V: Volume). Bitcoin historical data from Jan 2012 to March 2019 in 1-min intervals was downloaded from kaggle.

www.kaggle.com/mczielinski/bitcoin-historical-data

The data comes from Bitstamp, one of the major Bitcoin trading platforms. As a next step, the 1-min data was resampled to hourly data. Due to low liquidity in earlier BTC/USD trading-days, there were a few abnormal candlesticks in the data, which could not be found on other exchanges:



(a) (b)

Figure 6: Chart (a) shows an abnormal candlestick at 13:00 UTC on 6/23/2016. Similarly, one can see three such candlesticks in chart (b): Two at respectively 17:00 and 19:00 UTC on 4/16/2016 and one at 17:00 UTC on 4/17/2016.

Those candlesticks from Figure 6 were removed by replacing the low price of the candle by its open or close price.
Since the data from kaggle only contained data until March, additional Bitstamp BTC/USD data until May was downloaded from a different souce called CryptoCompare.

www.cryptocompare.com

Also, the hourly BTC/USD data from Gemini and the hourly BTC/USDT data from Bitfinex were downloaded from CryptoCompare. Those datasets were later used to see if the trading strategy remained consistent on different exchanges.

2.2 Backtesting of Basic Strategies

The Bitstmap hourly BTC/USD data was split up into in-sample and out-of-sample data. April 1st 2015 to April 1st 2018 was used as the in-sample data to backtest the strategies. Two time sections before and after the in-sample data, meaning June 1st 2013 to April 1st 2015 and April 1st 2018 to March 1st 2019 were used as out-of-sample data.

Backtesting was performed with the help of the python module from backtrader.com. All market orders were executed on the close-price of the candles which led to the trading signals. A fee of 0.2% for each trade was used, also accounting for slippage.

The two main statistics which were used to evaluate the performances of different strategies:

- **Sharpe Ratio**: The definition used in this thesis was

  $$\text{Sharpe Ratio} = \frac{\text{mean daily return}}{\text{annualized volatility}}, \tag{2}$$

  where annualized volatility is defined by

  $$\text{annualized volatility} = \text{standard deviation of daily return} \cdot \sqrt{365} \tag{3}$$

  since Bitcoin is traded every day of the year. As explained in section 1.2 the Sharpe ratio was the most important statistic for this thesis. That is because the higher the Sharpe ratio, the higher the risk-adjusted return of a strategy [16].

- **MAR Ratio**: Another way of measuring the risk-adjusted return that was used as defined in (4).

  $$\text{MAR} = \frac{\text{annualized return}}{\text{maximum drawdown}} \tag{4}$$

Other statistics which were measured to analyze and improve the strategies were:

- Return and Annual Return
- Number of Trades

– Maximum Drawdown

– Mean Return per Trade

– Win/Loss Ratio

– Average Holding Bars

As a starting point, the following four popular strategies were backtested over the in-sample data. Section 1.3.2 in the introduction explains the basics of those strategies, whereas this section defines the different period lengths which were used as parameters. If available, the standard periods for indicators were chosen, otherwise the periods were picked from personal trading experiences with almost no optimization. The signals were first tested for a long-only strategy.

1. MACD: The standard MACD(12, 26, 9) with period 12 for the fast EMA, period 26 for the slow EMA and period 9 for the signal-line. Both, the signals from the crossovers of the MACD with the signal-line and the signals from the MACD crossovers with the zero-line were backtested.

2. Moving Average Crossover: Periods 50 and 26 were tested for the slow moving average, respectively periods 20 and 12 for the fast moving average. The parameter combination (26, 12) was chosen, since the EMA-Crossover with these parameters has been backtested as well by demanding a crossover of the MACD with the zero-line.

3. Price Channel Break: Highest High (HH) and Lowest Low (LL) price channel with both having period 20 was used.

4. Bollinger Bands: Standard parameters, 20 for the moving average and 2 for the number of standard deviations (**std**), were used for the Bollinger Band strategy BB(per=20, std=2). For long-only signals both, the cross-up and cross-down of the candle-close with the upper band were used as entry-signals. The closing signal was triggered by a cross-down of a candle-close with the lower band. The short-only signals would be given exactly by the inverse.

These four strategies were combined with extra conditions that require a certain degree of volatility in Bitcoin's price before entering and exiting a position. Those conditions were either based on volume or the Bollinger

Band Width (BBW) as defined in (1). In order to quantitatively compare volatility over time, the two indicators were combined with moving averages as follows.

- Bollinger Band Width condition (**BBW_condition**): The BBW_condition is satisfied if the fast SMA (period 10) of the BBW is larger than the a slow SMA (period 50) of the BBW.

$$\text{BBW\_condition} = \text{SMA(BBW, per=10)} > \text{SMA(BBW, per=50)} \tag{5}$$

- Volume condition (**vol_condition**:) The vol_condition is met when the fast SMA (period 10) of the hourly volume is larger than the slow SMA (period 50) of the hourly volume.

$$\text{vol\_condition} = \text{SMA(volume, per=10)} > \text{SMA(volume, per=50)} \tag{6}$$

The backtests of these basic long-strategies can be found in section 6.1 in the Appendix.

2.3 Improving the Strategy

A basic long-only strategy with the best combination of Sharpe ratio and MAR ratio and the least drawdown was then picked to further improve. Individual trades were analyzed to find where drawdowns in the equity curves were coming from. The methods used to improve the trading signals and reduce the drawdowns were:

- **Stoploss**: An order that executes at market price to cut down losses. If one sets a stoploss at 5% below the trade was entered, one can not lose more than 5% (+ fees) in that particular trade.
- **Stopwin**: In order to lock in a certain percentage of gains one can set a stopwin. For example, if the gains of a trade are over 20%, one can set a stop order at 15% to have those gains locked in for sure.
- **Moving Average Confirmation**: An extra confirmation to enter a trade only when for example a faster moving average is over a slower moving average. Such a condition can make sense to verify if an uptrend is established before entering a long-trade. Another way of

confirmation could be a moving average cross-over. For example, a fast moving average crossing down a slower moving average can confirm a down trend. In our case, only four different SMAs with the following periods were used and they were referred to as:

- **sma_veryfast**: the fastest SMA with period=10
- **sma_fast**: SMA with period=20
- **sma_mid**: SMA with period=50
- **sma_slow**: SMA with period=100
- s**ma_veryslow**: the slowest SMA with period=200

Another indicator that was used was developed during the time of the thesis. It was named "Volatility-Level-Indicator", in short **VLI**. It contains four different lines, where one of them is the Bollinger Band Width (BBW) as defined by (1). To quickly refresh the mind of the reader, the BBW is calculated by taking the difference of the upper and lower Bollinger bands and dividing by the middle band. The three other lines in the VLI indicator can be directly derived from the BBW and they are defined as follows:

1. **VLI_fast**: The faster of the two moving averages used in the VLI, which can be calculated by

$$\text{VLI\_fast} = \text{SMA(BBW, per=200)}. \tag{7}$$

   Important to notice is, that the moving average uses BBW as the data parameter and not price.

2. **VLI_slow**: The slower moving average in the VLI, calculated by

$$\text{VLI\_slow} = \text{SMA(BBW, per=1000)}. \tag{8}$$

3. **VLI_top**: This VLI_top line was used to give a signal when the volatility - in this case represented by the BBW - was especially high. It is calculated by

$$\text{VLI\_top} = \text{SMA(BBW, per=1000)} + \text{2STD(BBW, per=1000)}. \tag{9}$$

   In words: The addition of two times the 1000-hour standard deviation of the BBW to the VLI_slow-line leads to VLI_top.

An indicator is best explained visually as in the following Figure 7. As the name already hints, the VLI was used to classify different volatility levels in price action. They were were defined as:

- **low_volatility_level**: VLI_fast < VLI_slow
- **high_volatility_level**: VLI_fast > VLI_slow
- **extreme_volatility**: BBW > VLI_top

Those volatility-regimes were used to impose different strengths of trend-confirmations by moving averages in order to enter a trade. The extreme_volatility case was on purpose not referred to as a level, because the condition for extreme volatility can be met at the same time as the low_volatility_level- or the high_volatility_level-condition.

Long-Short Strategy

The short-part of the strategy was only developed after the basic long-strategy was chosen and enhanced with the dfferent methods explained above. In order to best support the long strategy, similar signals as for the long-only strategy were backtested on the short-part. Backtest results of the different short-strategies in combination with the long-only strategy can be find in section 6.2.

After those improvements and being satisfied with the results and statistics of the long-short strategy, the out-of-sample data June 1st 2013 to April 1st 2015 and April 1st 2018 to March 1st 2019 were backtested. The results of those backtests can be found in the Results section 3.1 and 3.2.

New Strategy

As a last step to finalize the trading strategy, more data was treated as in-sample data. The new in-sample data was from April 1st 2015 to March 1st 2019, while June 1st 2013 to April 1st 2015 remained out-of-sample data. Again, the indicators from the last section 2.3 were used to improve the Sharpe and MAR ratios and to keep the drawdown as low as possible. Results of the new long-short strategy are displayed in the section 3.2.

Figure 7: The aim of this figure is to explain the volatility level indicator (VLI) in a more visual way. One can see the Bitcoin price from mid-April to mid-August and the VLI indicator below. The indicator consists of the standard Bollinger Band width (BBW) as defined by (1), which can be seen in red. The blue line is the VLI_fast line, defined as the 200 period SMA of the BBW. Similarly, the green line is the VLI_slow line, defined as the 1000 period SMA of the BBW. If the blue line is under the green line, the VLI would indicate a low_volatility_level. On the other hand, if the blue line is over the green line, the VLI would indicate a high_volatility_level. Extreme_volatility is reached, when the red BBW line is above the orange VLI_top line, which can happen during a high- or low_volatility_level. The VLI_top line is two 1000 period standard deviations of the BBW, in short 2STD(BBW, per=1000), above the green VLI_slow line. A few instances are marked by vertical blue dashed lines, where the red BBW crosses over the VLI_top. It can be observed, that the the crossover often happens at local peaks. Therefore, one might want to be extra careful to enter a trade at extreme_volatility.

2.4 Robustness and Consistency of the Strategy

Most of the effort went into finding a solid long-strategy. A robust long-strategy should not depend too much on the parameters used for the indicators. Otherwise, the chosen parameters might give a good result for the backtested data, but not for future data since market conditions can change. In order to verify if the long-only strategy was not too reliable on a particular set of parameters, a heat-map of the Sharpe ratios at different parameters was created. The heatmap was created for both, the original in-sample data from April 1st 2015 to April 1st 2018 and also the whole dataset from June 1st 2013 to March 1st 2019. Results can be viewed in section 3.4.

In order to see if the final strategy does not only work on Bitstamp, backtests were also performed on Gemini and Bitfinex. If the strategy is robust, results should stay consistent.

3 Results

The aim of this section is not only to present the result and performance of the final strategy of this paper, but to guide the reader through each extra step of sophistication that was added to enhance the strategy. As a starting point for the following long-only strategy, simple logical rules using Bollinger Bands and the volume condition were used. The strategy can also be found in secion 6.1 of the Appendix and is called BB+vol. In the following, this basic strategy is described as "Long 1". Every extra condition that was added to the logic is highlighted in green. All plots in this section contain both, the backtests of the in-sample and out-of-sample data. The different time-sections are subdivided by dashed lines in the plots, where the middle section contains the in-sample data. Some abbreviations are used in the logic, which are all explained in sections 2.2 and 2.3. Equity curves and results from the other basic strategies can be found in the Appendix.

3.1 Long Strategy

All pseudo-codes of the long strategy are listed step-by-step. The volume condition (vol_condition) which gets used often is defined by (6).

Long 1

```
if CrossDown Bollinger Top and vol_condition:
   long

if CrossDown Bollinger Bot and vol_condition:
   close
```

Long 2

```
if CrossDown Bollinger Top and vol_condition:
   long

if CrossDown Bollinger Bot and vol_condition:
   close

stoploss: at 5% below low of entry_candle
```

Long 3

```
if CrossDown Bollinger Top and vol_condition:
   long

if CrossDown Bollinger Bot and vol_condition:
   close

stoploss: at 5% below low of entry_candle
stopwin: if trade_profit over 20% add stopwin at 15%
         if trade_profit over 25% add stopwin at 20%
         if trade_profit over 30% add stopwin at 25%
         if trade_profit over 35% add stopwin at 30%
         if trade_profit over 40% add stopwin at 35%
```

Long 4

```
if CrossDown Bollinger Top and vol_condition:
   if close_price of candle > sma_fast (per20):
      long

if CrossDown Bollinger Bot and vol_condition:
   close

stoploss: at 5% below low of entry_candle
stopwin: if trade_profit over 20% add stopwin at 15%
         if trade_profit over 25% add stopwin at 20%
         if trade_profit over 30% add stopwin at 25%
         if trade_profit over 35% add stopwin at 30%
         if trade_profit over 40% add stopwin at 35%
```

Long 5

```
if CrossDown Bollinger Top and vol_condition:
    if close of price > sma_fast (per20):
        if BBW < VLI_top (#not extremely volatile):
            long

if CrossDown Bollinger Bot and vol_condition:
    close

stoploss: at 5% below low of entry_candle
stopwin: if trade_profit over 20% add stopwin at 15%
         if trade_profit over 25% add stopwin at 20%
         if trade_profit over 30% add stopwin at 25%
         if trade_profit over 35% add stopwin at 30%
         if trade_profit over 40% add stopwin at 35%
```

Long 6

```
if CrossDown Bollinger Top and vol_condition:
    if close of price > sma_fast (per20):
        if BBW < VLI_top:
            if low_volatility_level:
                if sma_mid (per50) > sma_verylow (per200):
                    long
            else:
                long

if CrossDown Bollinger Bot and vol_condition:
    close

#stoploss and stopwin like in Long 5
```

Long 7

```
if CrossDown Bollinger Top and vol_condition:
    if close of price > sma_fast (per20):
        if BBW < VLI_top:
            if low_volatility_level:
                if sma_mid (per50) > sma_verylow (per200):
                    long
            else:
                long
        elif sma_slow (per100) > sma_veryslow (per200):
            long
            stoploss at: low of last candle
            if trade_profit over 3% add stopwin at 1%

if CrossDown Bollinger Bot and vol_condition:
    close

#stoploss and stopwin like in Long 5
```

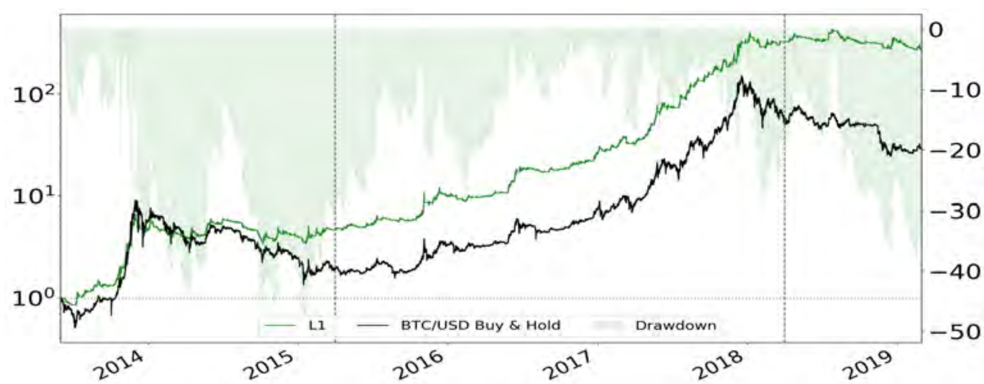
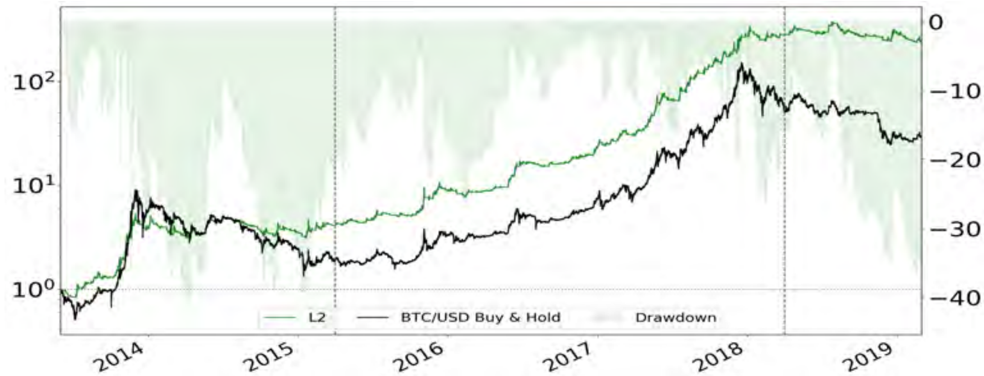
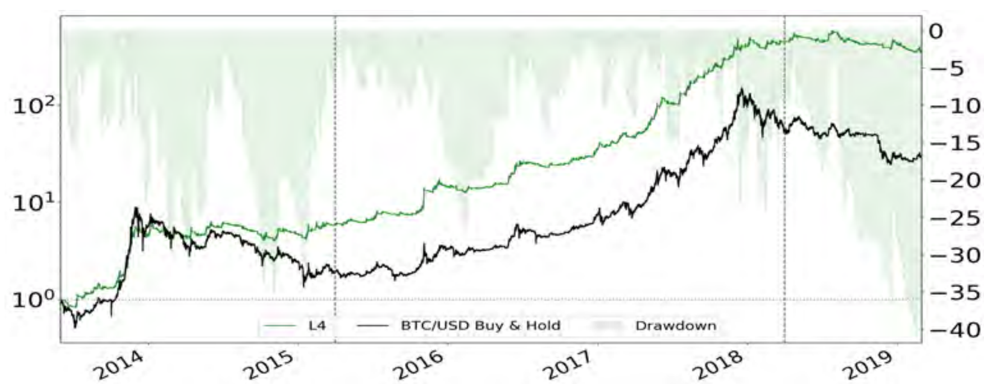


Figure 8: Long 1 – The equity curve of strategy L1 is displayed in dark-green together with the Bitcoin buy& hold benchmark for comparison. The logarithmic scale of the returns of the two curves is on the left axis. Drawdown as a function of time is displayed as a light-green area behind the curves with a scale on the right axis.



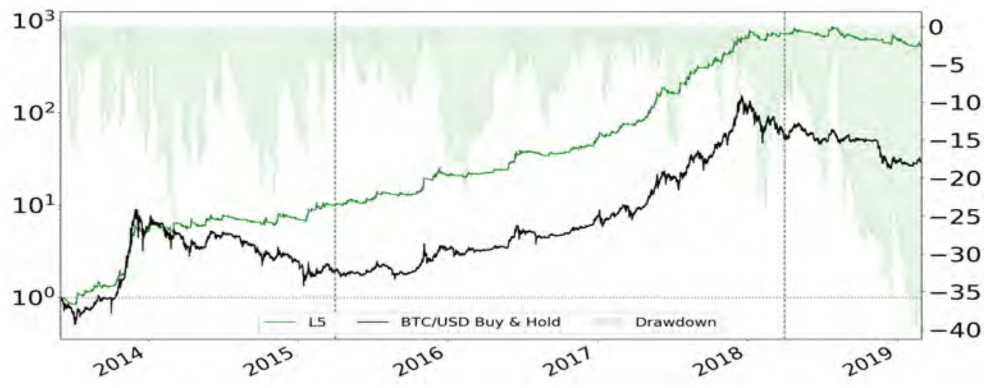
(a) Long 2

(b) Long 3

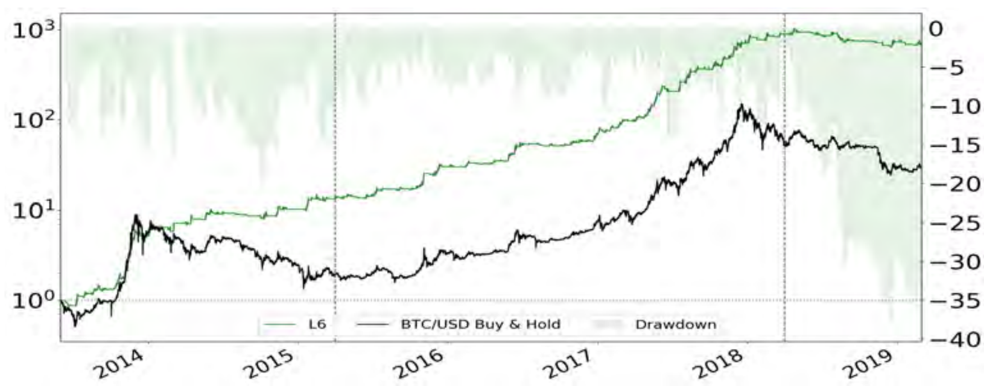


(c) Long 4

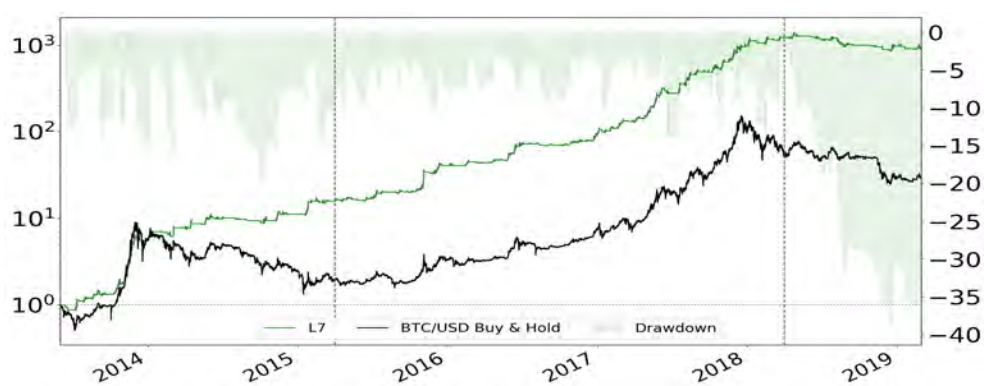
Figure 9: The equity curves of the three strategies L2, L3 and L4 in the same format as L1 in Figure 8.



(a) Long 5



(b) Long 6



(c) Long 7

Figure 10: The same format as in Figure 8 is used to show the equity curves of strategies L5, L6 and L7.

Backtests In-Sample Data: April 1st 2015 – April 1st 2018									
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Trades	Win/Loss Ratio	Mean Return	Average Hold Bars
Buy&Hold	1.84	2731.1%	204.5%	69.50%	2.94	-	-	-	-
L1	3.06	6959.0%	312.8%	29.14%	10.73	114	1.24	4.20%	120.2
L2	3.11	6753.2%	308.7%	27.59%	11.19	116	1.23	4.08%	116.6
L3	3.26	7513.3%	323.2%	27.42%	11.79	125	1.23	3.88%	104.5
L4	3.29	7708.1%	326.9%	27.42%	11.92	123	1.24	3.96%	104.7
L5	3.46	7135.1%	316.2%	24.46%	12.93	119	1.25	4.01%	105.6
L6	3.53	6682.3%	307.3%	14.80%	20.76	97	1.55	4.80%	102.8
L7	3.57	7771.6%	328.0%	14.80%	22.15	101	1.52	4.77%	103.0

Figure 11: The figure shows all the statistics derived from backtesting the Bitcoin in-sample data from April 1st 2015 to April 1st 2018.

Backtests Out-of-Sample Data: June 1st 2013 – April 1st 2015 and April 1st 2018 – March 1st 2019									
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Trades	Win/Loss Ratio	Mean Return	Average Hold Bars
B&H(13-15)	0.83	90.6%	42.2%	85.24%	0.49	-	-	-	-
L7 (13-15)	3.01	1469.3%	349.1%	21.59%	16.17	64	1.29	4.92%	74.3
B&H(18-19)	-0.62	-45.39%	-48.37%	68.35%	-0.71	-	-	-	-
L7 (18-19)	-0.80	-20.4%	-26.1%	39.44%	-0.66	28	0.33	-0.71%	66.2

Figure 12: This table shows the statistics of the final long strategy L7 tested on the two different out-of sample datasets.

The equity curve in Figure 8 together with the in-sample statistics from Figure 11 show that already the basic L1-strategy outperformed the BTC/USD benchmark in all aspects. Sharpe ratio, which was the most important statistic of this thesis, increased in-sample from 1.84 with the simplest buy and hold (B&H) strategy to over 3 with L1. The chart also shows that the strategy would not perform as well for the out-of-sample data. However, the maximum drawdown of around 50% is still better than the 80+% drawdown of Bitcoin in 2015 and 2019, as can be seen in Figure 1.
Chart (a) from Figure 9 shows the equity curve of strategy L2, which has an extra stoploss at the entry of each trade and panel (c) displays L3 with added stopwins. The stats tell tell us that the stoploss helped to reduce maximum drawdown a little. One can also see, by comparing the curves of L2 and L3, that the stopwins were helpful to realize more profit from short-term price spikes. The best example is the spike right at the end of 2015. This is also reflected in the statistics, where one can observe a big increase in return of the L3-strategy.
The chart (c) in Figure 9 shows the equity curve of strategy L4. The additional condition was that the close price of the candle has to be over the fast simple moving average at entry of the trade. Improvements over L3 are small and hardly visible by eye. The stats confirm that the main difference is a slight increase in the mean return per trade.
One can see that strategy L5 in chart (a) of Figure 10 has less drawdown compared to L4. This is visible in mid 2016 or the end of 2017 and especially in the first out-of sample data section. The improvement comes from the condition not to long when price action is extremely_volatile. One notices that this was the first time the VLI_indicator defined in section 2.3 was used. Even less drawdown can be observed in chart (b), which shows L6. The strategy was improved by imposing an extra moving average confirmation at low_volatile_levels. When volatility is low over a certain time, there is a danger to overtrade. This was one of the main factors for the bigger drawdown and it was improved a lot due to the extra moving average condition. Strategy L7 also allows buy-signals at extreme_volatility as defined in section 2.3, but imposes a strong moving average confirmation and at the same time sets a tight stoploss. L7 therefore makes four trades more than L6 and also has an increased return. An example where L7 makes one more good trade than L6 is shown in Figure 13.
To summarize the results for the in-sample-data: Both the Sharpe- and MAR-ratios improved from L1 to L7 by adding specific conditions to the strategy. Also the other statistics improved, such as a lower maximum drawdown and higher Win/Loss ratio.

If one takes a look at the out-of sample statistics in Figure 12, it can be seen that L7 still performed great from June 1st 2013 to April 1st 2015 with a Sharpe ratio of around 3 and a much lower drawdown of 22% compared to 85% by simply buy and holding. Also, the return of almost 1500% is a significant improvement. The performance during this time is similar and consistent with the in-sample-data. However, the result from backtesting L7 during the other out-of-sample section from April 1st 2018 until March 1st 2019 is not as good. Performance of the benchmark during this timeframe was bad as well, but the result of L7 is not consistent with all the statistics from before. In section 3.3, an improved new long-strategy with less drawdown in 2019 was proposed.

(a) Signals of strategy Long 6

(b) Signals of strategy Long 7

Figure 13: Bitcoin's hourly candle chart together with the VLI indicator defined in section 2.3. Chart (a) shows that as soon the red Bollinger Band width is over the orange VLI_top line, strategy L6 does not trigger long-signals anymore. With the extra condition to allow buying when it is very volatile (with strong confirmation and tight stoploss) L7 can profit more from this particularly big price move. This extra trade is visualized in chart (b).

3.2 Long-Short Strategy

In the following, one can see how the short strategy was developed by adding more conditions. The long-part of the long-short strategy stays Long 7 from the last section. Strategy LS1 will then be defined as the combination of L7 and Short 1, LS2 the combination of L7 and Short 2 etc.

Short 1

```
if CrossUp Bollinger Bot and vol_condition:
        short

stoploss at Highest High (per20)
if trade_profit over 10%: stoploss at HH (per10)
if trade_profit over 15%: stoploss at HH (per5)
```

Short 2

```
if CrossUp Bollinger Bot and vol_condition:
   if BBW < VLI_slow:
        short

#same closing conditions as in Short 1
```

Short 3

```
if CrossUp Bollinger Bot and vol_condition:
   if BBW < VLI_slow:
        short

stoploss at Highest High (per20)
if trade_profit over 10%: stoploss at HH (pe10)
if trade_profit over 15%: stoploss at HH (per5)
stopwin: if trade_profit over 25% add stopwin at 20%
         if trade_profit over 30% add stopwin at 25%
         if trade_profit over 35% add stopwin at 30%
         if trade_profit over 40% add stopwin at 35%
```

Short 4

```
if CrossUp Bollinger Bot and vol_condition:
    if BBW < VLI_slow:
        if sma_veryfast (per10) <  sma_mid (per50):
            short

stoploss at Highest High (per20)
if trade_profit over 10%: stoploss at HH (pe10)
if trade_profit over 15%: stoploss at HH (per5)

stopwin: if trade_profit over 25% add stopwin at 20%
         if trade_profit over 30% add stopwin at 25%
         if trade_profit over 35% add stopwin at 30%
         if trade_profit over 40% add stopwin at 35%
```

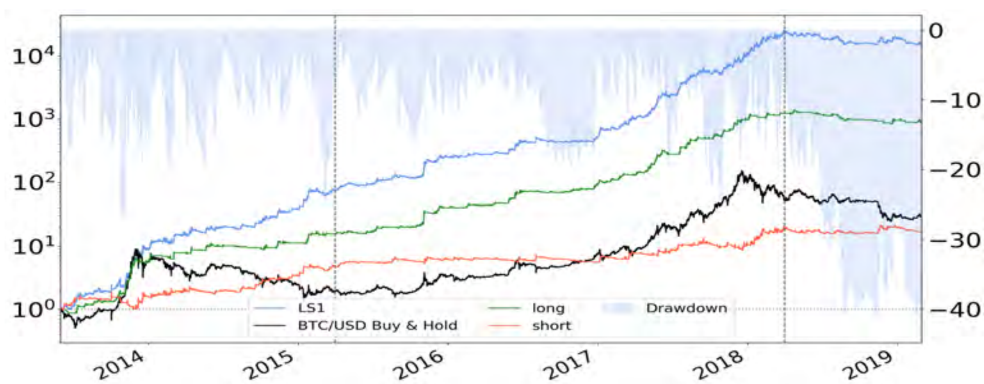
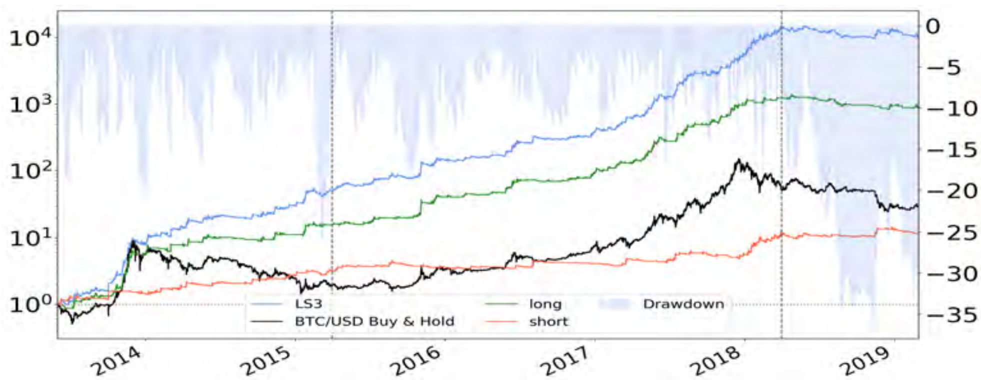
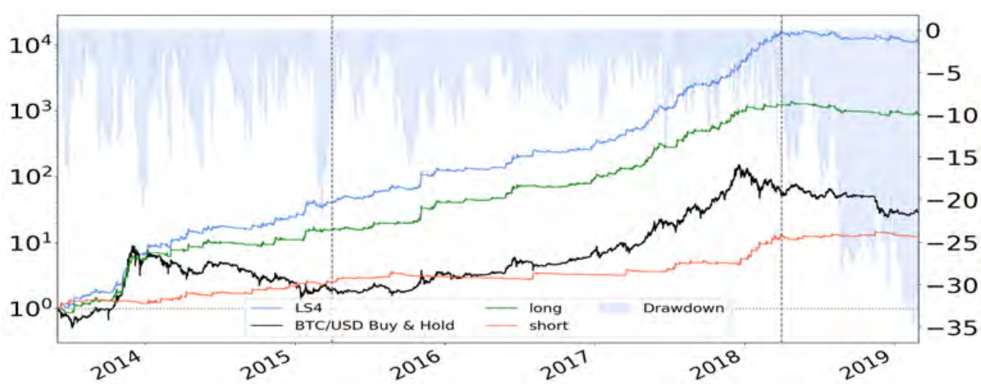


Figure 14: Long-Short 1 – The figure displays three different equity curves and the benchmark-line. The green line shows the performance of the long-only strategy L7 and the red curve shows the short-only part "Short 1". In blue the combination of long and short parts can be seen, which is called strategy LS1. Similarly as in the previous Figures 8 - 10, the logarithmic return scale of the curves is on the left. The drawdown-scale of the combined strategy LS1 is again on the right side.

(a) Long-Short 2



(b) Long-Short 3



(c) Long-Short 4

Figure 15: Same format as in Figure 14 is used to present the equity curves of strategies LS2, LS3 and LS4. Again, the long-strategy is L7 and LS2 uses "Short 2" as the short-part etc.

Backtests In-Sample Data: April 1st 2015 – April 1st 2018												
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Longs	Number Shorts	Win/Loss Long	Win/Loss Short	Mean Ret Long	Mean Ret Short	Av. Hold Bar
LS1	3.56	32839.6%	589.4%	24.55%	24.01	101	198	1.52	0.52	4.77%	0.85%	58.8
LS2	3.74	26245.1%	540.0%	18.19%	29.68	101	136	1.52	0.48	4.77%	1.01%	64.7
LS3	3.81	29143.3%	562.6%	18.19%	30.93	101	136	1.52	0.48	4.77%	1.1%	64.6
LS4	4.17	40519.0%	639.2%	16.03%	39.87	101	83	1.52	0.66	4.77%	2.19%	74.1

Figure 16: The table displays all the statistics retrieved from backtesting the different long-short strategies on the in-sample data.

Backtests Out-of-Sample Data: June 1st 2013 – April 1st 2015 and April 1st 2018 – March 1st 2019												
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Longs	Number Shorts	Win/Loss Long	Win/Loss Short	Mean Ret Long	Mean Ret Short	Av. Hold Bar
LS4 (13-15)	3.56	3861.5%	644.4%	22.44%	28.72	64	68	1.52	0.89	4.92%	1.48%	56.9
LS4 (18-19)	-0.81	-31.9%	-34.3%	34.70%	-0.99	33	41	0.32	0.41	-0.91%	-0.07%	46.8

Figure 17: Statistics from backtesting the strategy LS4 on the two different out-of-sample data sets.

The in-sample statistics of strategy LS1 in Figure 16 show that adding the simple short-strategy Short 1 to L7 kept the Sharpe Ratio at the same level, but drastically increased the return from around 7800% to almost three times more return with LS1. The strategy Short 1 (S1) used the inverse condition of the basic long-strategy L1 to open a short by use of a Bollinger Band crossover and the volume condition. However, it used a Highest High-stoploss/win to close the position.
An extra condition was added to S2, which demands that a short can only be opened if price action is not volatile - careful, this is not equal to the low_volatility_level condition from section 2.3. Statistics show that the return decreased, but Sharpe ratio and MAR ratio increased. Those statistics improved, because the maximum drawdown was reduced a lot by the end of 2017 as can be seen by comparing the equity curves of LS1 and LS2.
Performance improved slightly by using stopwins in LS3 and an even higher Sharpe and MAR ratio were achieved by adding an extra moving average confirmation for LS4. The statistics show that the last step cut the numbers of short-trades in half, but both the win vs. loss ratio and mean return per short increased significantly.
One can see in Figure 17, that similarly as already for L7, the performance of LS4 was solid during the first part of the out-of sample backtests. However, the strategy again performed poorly during the second part, which can also be seen in its equity curve. A new short-strategy in section 3.3.2 , which was developed by analyzing the trades during April 1st 2018 to March 1st 2019 has improved statistics.

3.3 New Strategy

The new strategy in this section was developed by changing the out-of sample data from April 1st 2018 until March 1st 2019 to in-sample data. This can also be seen in the following equity curves, where there is now only one dashed line subdividing in-sample and out-of-sample data.

3.3.1 New Long Strategy

Compared to the strategy Long 7, one extra confirmation was added to enter a trade at a high_volatility_level. The condition is highlighted in green:

New Long

```
if CrossDown Bollinger Top and vol_condition:
   if close of price > sma_fast (per20):
      if BBW < VLI_top:
         if low_volatility_level:
            if sma_mid (per50) > sma_verylow (per200):
               long
         elif not sma_veryslow > sma_slow
               > sma_mid: (#high_volatility_level)
            long
      elif sma_slow (per100) > sma_veryslow (per200):
         long
         stoploss at: low of last candle
         if trade_profit over 3% add stopwin at 1%

if CrossDown Bollinger Bot and vol_condition:
   close

stoploss: at 5% below low of entry_candle
stopwin: if trade_profit over 20% add stopwin at 15%
         if trade_profit over 25% add stopwin at 20%
         if trade_profit over 30% add stopwin at 25%
         if trade_profit over 35% add stopwin at 30%
         if trade_profit over 40% add stopwin at 35%
```

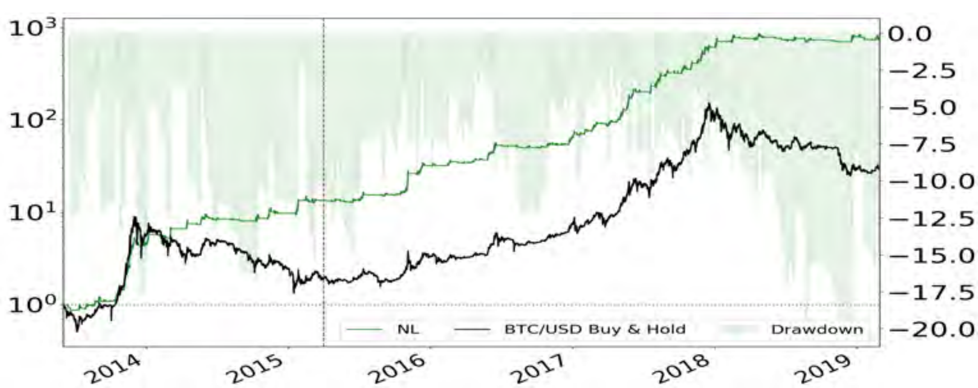


Figure 18: Same format as in previous equity curves. The equity curve and drawdown for the New Long strategy can be seen together with the Buy&Hold Benchmark.

Backtests In-Sample Data: April 1st 2015 – March 1st 2019									
Strat.	Sharpe Ratio	Return	Annual Return	Max DD	MAR Ratio	Num Trades	Win/ Loss	Mean Return	Av. Hold Bars
NL	2.80	5443.9%	178.7%	20.22%	8.84	117	1.02	3.84%	95.2

Figure 19: Statistics of the in-sample backtest of the NL strategy are displayed.

Backtests Out-of-Sample Data: June 1st 2013 – April 1st 2015									
Strat.	Sharpe Ratio	Return	Annual Return	Max DD	MAR Ratio	Num Trades	Win/ Loss	Mean Return	Av. Hold Bars
NL	2.94	1239.1%	311.9%	18.25%	17.09	58	1.42	5.09%	73.6

Figure 20: Statistics of the out-of-sample backtest of the NL strategy can be seen.

Compared to L7, the new long-strategy NL uses an extra moving average confirmation during a high_volatility_level to enter a trade. By comparing the equity curves of L7 in Figure 10 (c) and NL in Figure 18, it can be noticed that the extra condition helps to reduce the drawdown late 2018 and in 2019. An example of how the condition prevents some bad trades can be studied in Figure 21: The chart shows three trades, which the algorithm executed because price crossed down the upper Bollinger band while the fast moving average of the volume was over the slower one. One can see that all three trades lost money. The VLI indicator, as defined in (7) to (9), shows that all trades happened during a phase where the blue VLI_fast - line was over VLI_slow in green. This is hardly visible for the first entry signal, which is marked by a green arrow, but all trades were executed during a high_volatility_phase. Since the veryslow_sma was above the slow_sma, which was again over the mid_sma (orange line in the price chart over green line and green line over blue line) those long-signals clearly happened during a downtrend. With the extra condition in the new long strategy, those signals did not get triggered anymore and it reduced the drawdown.

The stats from Figure 20 show that the NL out-of-sample backtest from June 1st 2013 to April 1st 2015 still gave a similarly good result as for L7.

Figure 21: Losing trades of strategy L7 – A chart in order to explain three losing trades that happened during 2019, which were part of the reason of the big drawdown of strategy L7 as defined in chapter 3.1. Displayed is a Bitcoin hourly candle chart on top with green and red arrows as trading signals and the volume_condition indicator as defined by 6 in the middle. On the bottom the VLI indicator, which was explained in section 2.3, is plotted. In the chart one can also see three simple moving averages with different period lengths and the Bollinger bands in red.

3.3.2 New Long-Short Strategy

In the following, the new long-short strategy with in-sample data from April 1st 2015 to March 1st 2019 is presented. Since the New Long-strategy from above was used as the long-part, only the different conditions added to the short strategy are shown. The closing conditions in the new strategy stayed the same, while the entry signal for a short depended on a cross-over signal this time.

New Short 1

```
if CrossUp Bollinger Bot:
    wait for sma_slow (per100) CrossDown sma_mid(per50):
        if BBW < VLI_top (#not extremely volatile):
            short

stoploss at Highest High (per20)
if trade_profit over 10%: stoploss at HH (per10)
```

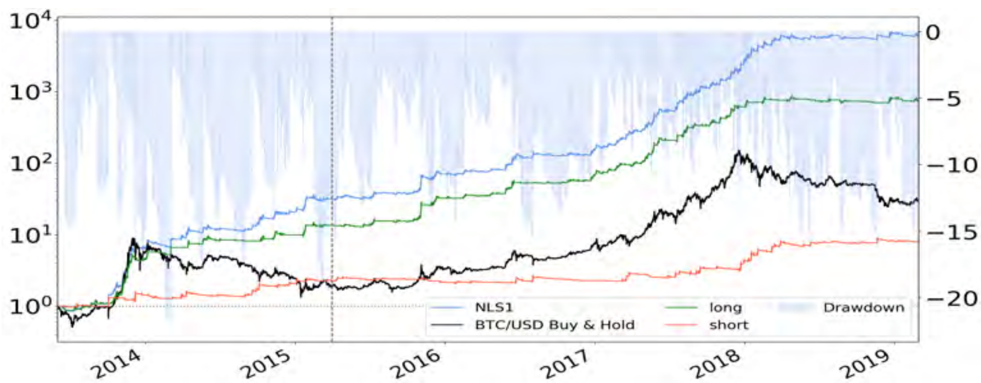
```
if trade_profit over 15%: stoploss at HH (per5)

stopwin: if trade_profit over 25% add stopwin at 20%
         if trade_profit over 30% add stopwin at 25%
         if trade_profit over 35% add stopwin at 30%
         if trade_profit over 40% add stopwin at 35%
```

New Short 2

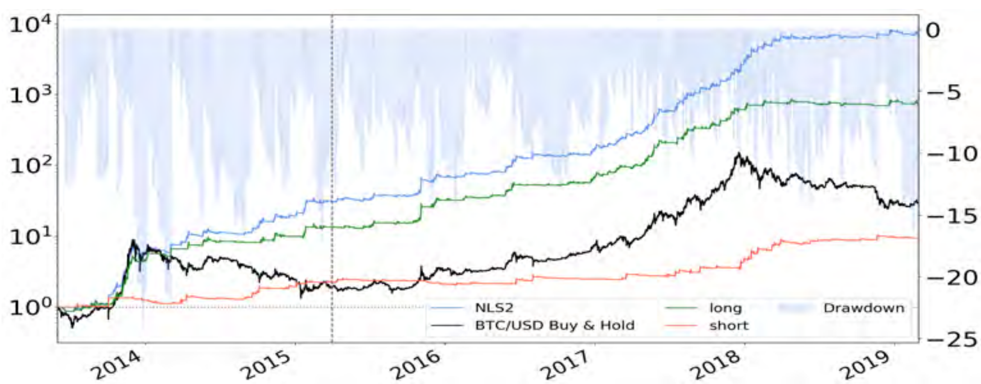
```
if CrossUp Bollinger Bot:
    if BBW < VLI_slow:
        wait for sma_slow CrossDown sma_mid:
            if BBW < VLI_top:
                short

#stoploss and stopwin same as in New Long-Short 1
```

The equity curve of NLS1 in Figure 22 (a) shows that by treating the the data from April 1st 2018 to March 1st 2019 also as in-sample, it was possible to severely reduce the drawdown during 2019. Comparing statistics from Figure 17 and Figure 23 show that while LS4 had a drawdown of about 35% during 2019, the new long and short strategies reduced it to around 15%.
Figure 23 also shows that compared to NLS1, the strategy NLS2 has an increased mean return for short trades of about 0.4% and therefore also the other statistics were improved over NLS1. The extra condition used for this enhancement was that volatility should be low at the time at which price crosses up the Bollinger bottom band - not to be confused with low_volatility_level.
Both new short strategies demanded a slow moving average crossing down a faster moving average before entering a short trade. In comparison, the earlier short strategies only required the slower moving average to be above the faster one. It can also be noticed that the new short strategies did not use a volume_condition. How the changes, especially the crossover-condition, helped to get more reliable short-signals is visualized by a comparison of Figures 25 and 26.
The chart in Figure 25 shows some of the trades triggered by the old long-short strategy LS4, which were responsible for the drawdown in 2019. Three so-called "fakeouts" happened, where the short-signals get triggered since

all necessary conditions are met and then a quick reversal to the upside happens, preventing an opportunity to close the trade in profit. In Figure 26, where the signals of NLS2 for the same time span are plotted, only one such fakeout can be noticed and the second trade could be closed in profit.



(a) New Long-Short 1



(b) New Long-Short 2

Figure 22: Same format as is used to present previous long-short equity curves of. The green long-only part is still the new long strategy NL. Chart (a) uses the new Short 1 (NS1) strategy as the short-part and chart (b) uses NS2.

Backtests In-Sample Data: April 1st 2015 – March 1st 2019												
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Longs	Number Shorts	Win/Loss Long	Win/Loss Short	Mean Ret Long	Mean Ret Short	Av. Hold Bar
New LS1	3.03	19270.6%	283.5%	16.58%	17.10	117	136	1.02	0.42	3.81%	1.06%	59.0
New LS2	3.17	22989.01%	301.09%	16.09%	18.71	117	109	1.02	0.45	3.81%	1.48%	63.2

Figure 23: Statistics of the in-sample backtest of the new long-short strategies.

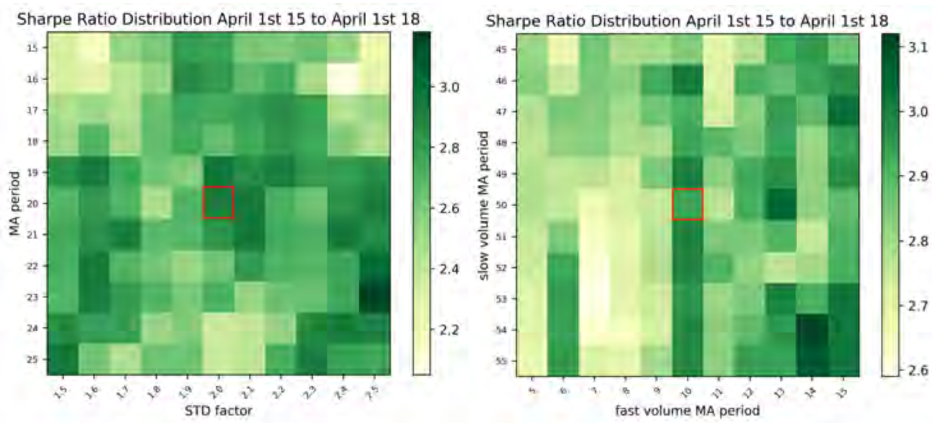
Backtests Out-of-Sample Data: June 1st 2013 – April 1st 2015												
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Longs	Number Shorts	Win/Loss Long	Win/Loss Short	Mean Ret Long	Mean Ret Short	Av. Hold Bar
New LS2	3.32	2963.59%	546.95%	24.12%	22.67	57	51	1.48	0.65	5.21%	1.77%	54.6

Figure 24: The out-of-sample backtest statistic of the final long-short strategy LS2.

Figure 25: Losing Trades in LS4 – The signals which can be seen are triggered by the old LS4 strategy. Almost identical to Figure 21, the Bitcoin hourly candle chart with the volume- and VLI-indicator below are shown. Differences are that the three displayed trades are short trades, so the red arrows mark the entries of the trades. Also, instead of the 200 period veryslow_sma, the orange 20 period Higher High line which triggered the closing signals is shown in the candle-chart.

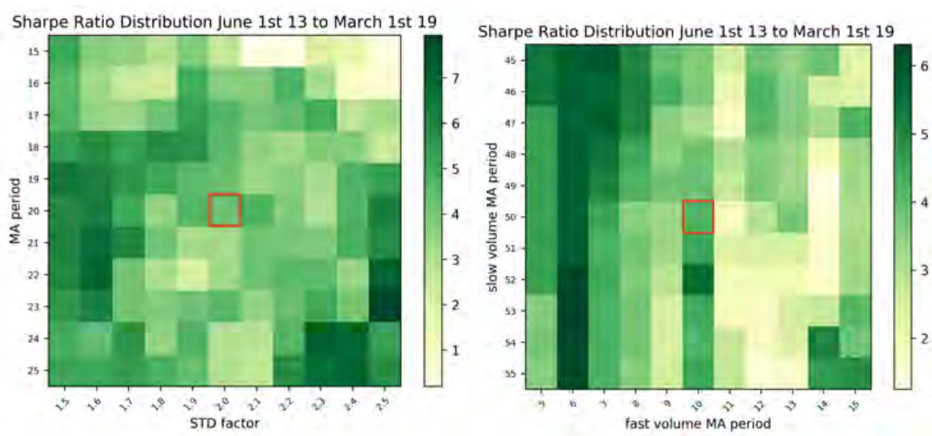
Figure 26: Improvements of NLS2 – Signals are triggered by the new NLS2 strategy. Same layout as in 25.

3.4 Robustness of the Long Strategy



(a) Bollinger parameters **(b)** Volume condition parameters

Figure 27: The heatmaps show an in-sample stability test of the basic long strategy L1 by calculating the Sharpe ratio for different parameters. Marked in red is the result which corresponds to the originial parameters chosen for L1. Heatmap (a) shows how other parameters for the Bollinger Bands, where STD stands for standard deviation, change the Sharpe ratio. Also, one can see in (b) how other moving average parameters in the volume condition as defined by (6) influences the Sharpe ratio of L1.



(a) Bollinger parameters **(b)** Volume condition parameters

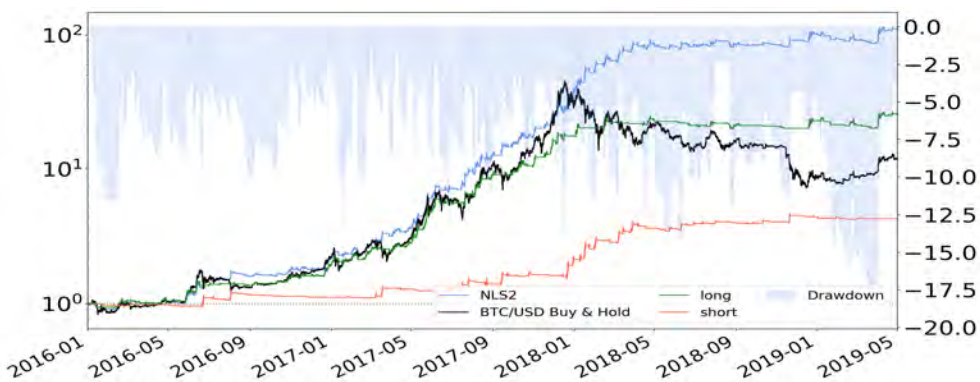
Figure 28: Same format as for the last Figure 27 is used, but this time the backtests included the in-sample & out-of-sample data together.

The heatmaps in Figures 27 and 28 show how the Sharpe ratio of the basic long strategy L1 depends on different sets of parameters. In Figure 27 (a) the heatmap for the in-sample backtest with constant periods for the volume condition, but different parameters for the Bollinger Bands is shown. Marked with a red frame is the Sharpe ratio resulting from the backtest with chosen standard parameters. It can be seen that the chosen parameters for the basic long-strategy L1 were in the better range of the spectrum, but other choices would have even improved the Sharpe ratio.
Heatmap (b) of the same Figure 27 shows how the Sharpe ratio changed for different periods in the volume condition as defined in (6). In this case the performance of the strategy seems more sensitive to parameter changes. Especially, parameters to the left of the red framed field performed worse compared to those more on the right. This behaviour indicates that a more sensitive volume condition with a smaller period for the fast moving average damages the performance. At least, for parameters close to the red marked field Sharpe ratios were still above 2.5 in both (a) and (b).
Figure 28 shows the same heatmaps, but for the in-sample and out-of-sample data together - meaning from June 1st 2013 to March 1st 2019. Heatmap (a) in Figure 28 looks similar to the in-sample result of the Bollinger parameters, but with a greater variation in Sharpe ratios: The circumference of the parameter space around the red framed field at which Sharpe ratios are greater than 2 contracts.
Of notice is also that in Figure 28 (b), the Sharpe ratio dropped on average for slower periods of the fast moving average, while it is the other way around in Figure 27 (b).

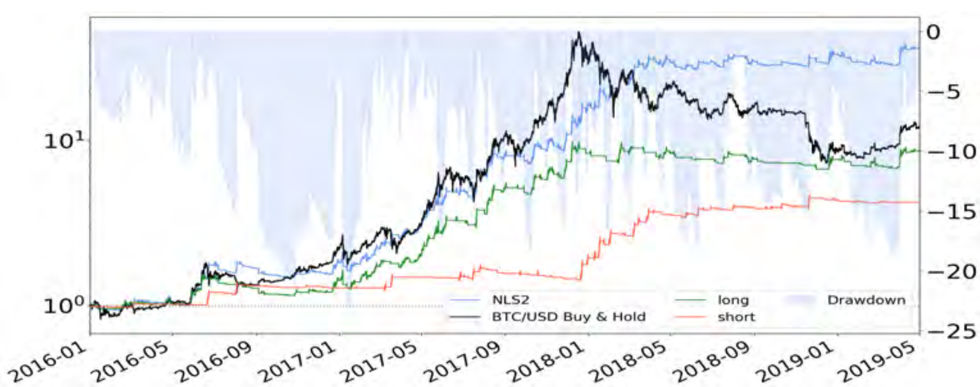
3.5 Consistency on Different Exchanges

In Figures 29 and 30 the backtests of the final strategy NLS2 on different Bitcoin exchanges can be seen. The equity curve in Figure 29 (a) again shows the performance of the strategy on Bitstamp , but this time with data from the cryptocompare source. Minor differences in the data can be noticed from the values in the drawdown if compared to the backtest on the kaggle source in Figure 22 (b). The chart was displayed, because it now includes the two extra months April and May. It can be observed that the strategy catched the momentum from Bitcoin's recent recovery and performed similarly well as the benchmark.
Equity curves of the same NLS2 strategy on Gemini exchange are displayed in chart (b) of Figure 29. It can be seen that there was more drawdown by the end of 2016 compared to Bitstamp and the long strategy had less return.

Other than that, the result was similar to the one from Bitstamp.
If one compares the performances of NLS2 on Bitstamp and Gemini to Bitfinex in Figure 30, one can see a similarity of the drawdowns in the years 2016 and 2017. However, the big Bitfinex drawdown in 2019 is inconsistent with the other two results.



(a) New Long Short 2 (NLS2) strategy on Bitstamp exchange



(b) NLS2 backtested on Gemini exchange

Figure 29: The equity curves of the final strategy New Long Short 2 backtested on different exchanges. The same format is used as for earlier charts.

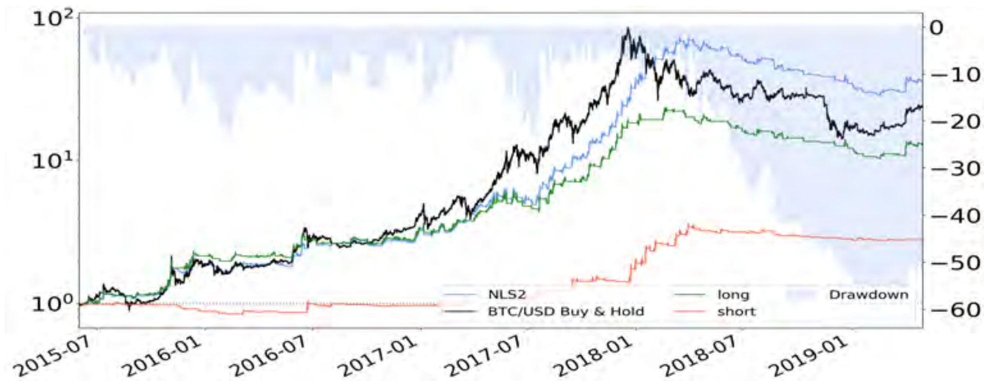


Figure 30: Backtest of final strategy NLS2 on Bitfinex – NLS2 backtested on Bitfinex exchange, where a major drawdown from mid-2018 all the way to the end of the backtesting period can be noticed.

4 Discussion

The strategy which was found using the original in-sample data from April 1st 2015 to April 1st 2018 was Long Short 4 (LS4). Technically, the strategy already satisfied the set goal of a higher risk-adjusted return compared to the benchmark. From a look at the blue performance line in Figure 15 (c), hardy anyone who would have started to use the algorithm from June 1st 2013 on would have complained about the returns and drawdowns compared to Bitcoin. The problem is however, that a trader who does not know about this great result from the past, could start using the algorithm in the middle of 2018. In a very short time one would suffer a massive 35% drawdown. Sure, during the time of this drawdown Bitcoin was in a bear market. But if the strategy was robust, the performance during 2018 and 2019 should be comparable to the results from the last bear market in 2014 and 2015, which is clearly not the case. To see which trading signals caused the problem, more data was added to the in-sample data and the strategy was improved. That should better explain why a new strategy was developed.

During the thesis, most effort was invested into finding a solid long strategy. The final algorithm, called New Long (NL), can be found in section 3.3.1. One notices how the volatility level indicator (VLI) was used to set different moving average confirmations for all defined levels of volatility. In comparison, the final short strategy New Short 2 from section 3.3.2 is less sophisticated and a short trade can only be entered at low volatility. The red equity curve in Figure 22 shows that the strategy stayed mostly flat during the bull market of 2016 and 2017, which is positive. However, it also stayed flat a lot of the time during the two bear markets. For example, it was not able to capture much profit from Bitcoin's big crash at the end of 2018. If there was more time at hand, the short strategy could have been improved similarly to the New Long strategy. By imposing different confirmation strengths at the different volatility levels and using extra soplosses or stopwins, the strategy could have probably been improved.

4.1 Bitfinex Inconsistency

In section 3.5 the backtests of the final strategy NLS2 performed similarly well on Gemini as on Bitstamp. Striking is however the big drawdown that happened during the end of 2018 and 2019 on Bitfinex, as can be seen in Figure 30. A possible reason for the difference in performance could be that the Bitfinex trading-pair for Bitcoin is not really BTC/USD, but actuall

BTC/USDT [28]. USDT is the tickersymbol of tether, which is marketed as a cryptocurrency one to one pegged to the dollar. Tether states on the official website that USDT is 100% backed by traditional currency or cash equivalents and, from time to time, also by other assets [29]. The USDT/USD chart in Figure 31 paints a different picture and shows that the USDT-price varied quite a bit over time and for example stayed below $1 for more than two months from October 2018 on.

Figure 31: USDT/USD daily candle chart from mid 2018 to June 2019 on Bittrex exchange. USDT is the ticker symbol for tether, a cryptocurrency that should always be worth $1.

If one analyses in detail where the drawdown comes from, one finds that many trading signals were different on Bitfinex compared to Bistamp. During mid-November 2018 there was unusual volatility in tethers price. A comparison between Figures 32 and 33 shows a trading signal during that time which was executed on Bitstamp, but not on Bitfinex. The Bitstamp chart in Figure 32 shows how the slower green moving average in the candle chart crossed down the blue faster moving average, which was a necessary condition to signal a short entry. On the other hand, this crossover did not happen in the Bitfinex candle chart of Figure 33. Another factor, which had an impact on the difference in trading signals was the volume condition as defined by (6). The Bitstamp and Bitfinex volume profiles looked different in some cases and since the strategy is very dependent on this condition, trading signals can change quickly. Probably this inconsistency also happened indirectly because of the extra volatility in the USDT price. More discussion on the volume condition can be found in the next section.

Figure 32: Crossover on Bitstamp – Identical to Figure 25, the Bitstamp Bitcoin hourly candle chart with the Volume- and VLI-indicator below are shown. The entry and exit signals of the visible short trade were triggered by the strategy NLS2 as explained in section 3.5. The entry signal only happened because of the green 100 period SMA crossing down the blue 50 period SMA.

Figure 33: No crossover on Bitfinex – Same layout as in 32. This time however, one can see that there is no crossover between the green and blue moving averages in the price chart. Therefore no trade happened.

4.2 Robustness of the Strategy

As discussed above, the Bitfinex BTC/USDT chart shows differences in price action and volume compared to the BTC/USD charts on Bitstamp and Gemini. However, a robust trading strategy should not depend so much on those small changes and still perform well. The volume condition, as defined by equation (6), was used in the entry and also exit conditions for long trades. Figures 27 (b) and 28 (b) show the in-sample and in- & out-of-sample robustness tests of the volume condition. One notices that the Sharpe ratio of the basic long strategy L1 was sensitive to the parameter choice of the fast moving average in the volume condition. In-sample, the Sharpe ratio became worse for a slight parameter shift to the left, while it got worse for a parameter shift to the right for in-& out-of-sample together. The sensitivity and asymmetry of the results show that this condition, to only enter and exit a trade at relatively high volume, is not robust. The statistics in Figure 35 of the Appendix show that the Bollinger Band strategy without the volume condition (BB 2) made 274 trades as opposed to 114 trades together with the volume condition (BB+vol). This means that the extra condition prevented 160 trades, which is a big number. Sure, the win/loss ratio and mean return of the trades improved, but certainly there were also good trading signals that were filtered out. In the aftermath, it would have made sense to include these trades in the strategy as well, but with stricter other confirmations.

A way to increase the robustness of the strategy would be by running different individual strategies in parallel. If one strategy takes a loss, one of the others could make up for it. Similarly as a diversification in different assets makes sense from an investment perspective, one should seek a diversification in strategies for more robustness.

5 Conclusion

Thanks to the trading strategy, the risk-adjusted return and therefore the Sharpe ratio increased to a much higher level compared to the benchmark. If backtested over the whole Bitstamp data set from April 1st 2013 to March 1st 2019, the Sharpe ratio increased to a value of 3.2 compared to a Sharpe of 1.13 with a simple buy & hold strategy. Also, compared to the maximum drawdown of the benchmark of over 85%, one would have only suffered a maximum drawdown of about 25% with the strategy. In accordance with the works from Luisanna Cocco *et al.* [12] and Kamil Żbikowski [14], the results of the final strategy clearly confirm the hypothesis that the the Bitcoin market is still very inefficient. The potential return over the backtested period would far surpass reasonable returns known from other financial markets.

As we have discussed, there are some questions in the robustness of the final strategy of the thesis and therefore it still has to be seen as a prototype. How would one go ahead to make the algorithm more robust and actually bring it into production to automatically trade Bitcoin? One can develop a variaty of individual strategies by improving more of the different basic strategies, which were backtested in the Appendix. Most of the ideas in the final strategy of this thesis, such as the different volatility levels, could certainly be used to also improve other signals. Running in parallel several individual strategies, maybe more simple in logic, would certainly increase robustness. Also, one can choose not just one set of parameters, but several different ones.

At the time of writing it seems as if the Bitcoin bear market of 2018 and 2019 is finally coming to an end. To profit best possible from the next bull market, the next goal will be to design and implement a robust Bitcoin trading bot with all the knowledge that has been gained during this thesis.

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Die unterzeichnete Eigenständigkeitserklärung ist Bestandteil jeder während des Studiums verfassten Semester-, Bachelor- und Master-Arbeit oder anderen Abschlussarbeit (auch der jeweils elektronischen Version).

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Backtesting of Trading Strategies for Bitcoin

Verfasst von (in Druckschrift):

Bei Gruppenarbeiten sind die Namen aller Verfasserinnen und Verfasser erforderlich.

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Zürich, 11.06.2019	A. Glücksmann

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6 Appendix

As explained in the methodology, several popular trading strategies were backtested and the strategy with the best overall statistics - most importantly a high Sharpe ratio - was further developed. In the following, the algorithms and results for some of those strategies can be viewed. More combinations of different conditions were backtested, but the most relevant ones are displayed.

6.1 Basic Long Strategies

The strategy from this section which was chosen to further develop was BB+vol.

MACD 1

```
if MACD CrossUp signal_line:
    long

if MACD CrossDown signal_line:
    close
```

MACD 2

```
if MACD CrossUp zero_line:
    long

if MACD CrossDown zero_line:
    close
```

MACD+BBW

```
if MACD > 0 and BBW_cond: #BBW_cond defined in (5)
    long

if MACD < 0 and BBW_cond:
    close
```

MACD+vol

```
if MACD > 0 and vol_cond: #vol_cond defined in (6)
    long

if MACD < 0 and vol_cond:
    close
```

SMA 1

```
if sma_fast (period 20) CrossUp sma_mid (period 50):
    long

if sma_fast (period 20) CrossDown sma_mid (period 50):
    close
```

SMA 2

```
if sma (period 12) CrossUp sma (period 26):
    long

if sma (period 12) CrossDown sma (period 26):
    close
```

SMA+BBW

```
if sma (per=12) > sma (per=26) and BBW_cond:
    long

if  sma (per=12) > sma (per=26) and BBW_cond:
    close
```

SMA+vol

```
if sma (per=12) > sma (per=26) and vol_cond:
    long

if  sma (per=12) > sma (per=26) and vol_cond:
    close
```

Price Channel (PC)

```
if close of candle > Highest High (per=20):
    long

if close of candle < Lowest Low (per=20):
    close
```

PC+BBW

```
if close of candle > Highest High (per=20) and BBW_cond:
    long

if close of candle < Lowest Low (per=20) and BBW_cond:
    close
```

PC+vol

```
if close of candle > Highest High (per=20) and vol_cond:
    long

if close of candle < Lowest Low (per=20) and vol_cond:
    close
```

Bollinger Bands 1 (BB 1)

```
if CrossUp Bollinger Top;
    long

if CrossDown Bollinger Bot:
    close
```

BB 2

```
if CrossDown Bollinger Top;
    long

if CrossDown Bollinger Bot:
    close
```

BB+BBW

```
if CrossDown Bollinger Top and BBW_cond:
    long

if CrossDown Bollinger Bot and BBW_cond:
    close
```

BB+vol

```
if CrossDown Bollinger Top and vol_cond:
    long

if CrossDown Bollinger Bot and vol_cond:
    close
```

Backtests MACD In-Sample Data: April 1st 2015 – April 1st 2018									
Strategy	Sharpe Ratio	Return	Annual Return	Max DD	MAR Ratio	Num Trades	Win/ Loss	Mean Return	Av. Hold Bars
MACD 1	-0.54	-73.9%	-35.8%	80.43%	-0.45	1034	0.43	-0.08%	13.0
MACD 2	1.43	628.7%	92.7%	48.52%	1.91	447	0.43	0.56%	34.7
MACD +BBW	2.35	3310.2%	220.9%	36.94%	5.98	180	0.82	2.26%	84.6
MACD +vol	2.05	1874.1%	167.8%	35.03%	4.79	251	0.62	1.41%	58.9

(a) MACD backtests

Backtests SMA In-Sample Data: April 1st 2015 – April 1st 2018									
Strategy	Sharpe Ratio	Return	Annual Return	Max DD	MAR Ratio	Num Trades	Win/ Loss	Mean Return	Av. Hold Bars
SMA 1	1.69	952.2%	117.6%	57.04%	2.06	295	0.77	0.97%	52.0
SMA 2	1.82	1303.3%	139.3%	44.72%	3.11	569	0.58	0.55%	26.1
SMA +BBW	2.75	6859.2%	306.1%	33.71%	9.08	198	1.08	2.44%	79.4
SMA+vol	2.47	3455.2%	225.3%	28.28%	7.97	293	0.69	1.4%	47.3

(b) SMA backtests

Backtests Price Channel In-Sample Data: April 1st 2015 – April 1st 2018									
Strategy	Sharpe Ratio	Return	Annual Return	Max DD	MAR Ratio	Num Trades	Win/ Loss	Mean Return	Av. Hold Bars
PC	1.80	1321.9%	140.3%	37.50%	3.74	233	0.82	1.35%	68.1
PC+BBW	2.01	1984.3%	172.7%	29.57%	5.84	81	1.25	4.6%	196.8
PC+vol	2.56	4298.5%	249.0%	29.26%	8.51	112	1.04	3.96%	138.3

(c) Price Channel backtests

Figure 34: All the statistics for the backtests of the different basic long-only strategies.

Backtests Bollinger Bands In-Sample Data: April 1st 2015 – April 1st 2018									
Strategy	Sharpe Ratio	Return	Annual Return	Max DD	MAR Ratio	Num Trades	Win/ Loss	Mean Return	Av. Hold Bars
BB 1	1.49	613.3%	91.4%	52.84%	1.73	274	0.67	0.85%	49.5
BB 2	1.49	589.4%	89.2%	51.89%	1.72	274	0.68	0.83%	47.3
BB+BBW	2.35	2266.8%	184.4%	29.98%	6.15	76	1.62	4.9%	183.3
BB+vol	3.05	6959.0%	308.0%	29.14%	10.57	114	1.24	4.2%	120.2

Figure 35: Bollinger Bands backtests

6.2 Basic Long-Short Strategies

This section of the appendix shows some of the basic backtests to find a long-short strategy. The long-part of the strategy is always Long 7 from the Results section 3.1. Strategy BB+HH+vol was chosen as a long-short strategy to go more in detail.

MACD 1

```
if MACD CrossDown signal_line:
    short

if MACD CrossUp signal_line:
    close
```

MACD 2

```
if MACD CrossDown zero_line:
    short

if MACD CrossUp zero_line:
    close
```

MACD+BBW

```
if MACD < 0 and BBW_cond: #BBW_cond defined in (5)
    short

if MACD CrossUp zero_line:
    close
```

MACD+vol

```
if MACD < 0 and vol_cond: #vol_cond defined in (6)
    short

if MACD CrossUp zero_line:
    close
```

SMA1

```
if sma_fast (period 20) CrossDown sma_mid (period 50):
    short

if sma_fast (period 20) CrossUp sma_mid (period 50):
    close
```

SMA2

```
if sma_fast (period 12) CrossDown sma_mid (period 26):
    short

if sma_fast (period 12) CrossUp sma_mid (period 26):
    close
```

SMA+BBW

```
if sma (per=26) > sma (per=12) and BBW_cond:
    short

if sma_fast (period 12) CrossUp sma_mid (period 26):
    close
```

SMA+vol

```
if sma (per=26) > sma (per=12) and vol_cond:
    short

if sma_fast (period 12) CrossUp sma_mid (period 26):
    close
```

Price Channel (PC)

```
if close of candle < Lowest Low (per=20):
    short

stoploss at Highest High (per=20)
```

PC+BBW

```
if close of candle < Lowest Low (per=20) and BBW_cond:
    short

stoploss at Highest High (per=20)
```

PC+vol

```
if close of candle < Lowest Low (per=20) and vol_cond:
    short

stoploss at Highest High (per=20)
```

BB

```
if CrossUp Bollinger Bot:
    short

if CrossUp Bollinger Top:
    close
```

BB+BBW

```
if CrossUp Bollinger Bot and BBW_cond:
    short

if CrossUp Bollinger Top:
    close
```

BB+vol

```
if CrossUp Bollinger Bot and vol_cond:
    short

if CrossUp Bollinger Top:
    close
```

BB+HH+vol

```
if CrossUp Bollinger Bot and vol_cond:
    short

stoploss at Highest High (per=20)
```

Long-Short Backtests, MACD, In-Sample Data: April 1st 2015 – April 1st 2018												
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Longs	Number Shorts	Win/Loss Long	Win/Loss Short	Mean Ret Long	Mean Ret Short	Av. Hold Bar
MACD 1	1.83	1726.8%	163.1%	42.02%	3.88	102	581	1.49	0.33	4.68%	-0.2%	24.8
MACD 2	2.24	3509.8%	230.1%	35.92%	6.41	100	306	1.5	0.28	4.79%	-0.17%	44.9
MACD +BBW	2.67	6905.9%	311.7%	24.40%	12.78	100	189	1.5	0.45	4.79%	0.05%	57.7
MACD +VOL	2.30	3882.0%	241.1%	38.35%	6.29	101	251	0.54	0.34	4.69%	-0.15	50.6

Figure 36: Backtests of different MACD signals for the short-part together with L7 as the long-part of the strategy.

Long-Short Backtests, SMA, In-Sample Data: April 1st 2015 – April 1st 2018												
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Longs	Number Shorts	Win/Loss Long	Win/Loss Short	Mean Ret Long	Mean Ret Short	Av. Hold Bar
SMA 1	2.10	2540.6%	197.5%	40.18%	4.92	96	214	1.34	0.46	4.28%	-0.11%	58.2
SMA 2	2.64	7228.1%	317.9%	32.66%	9.73	97	378	1.55	0.42	4.88%	0.06%	38.1
SMA+BBW	3.06	12434.7%	399.7%	24.58%	16.26	99	216	1.48	0.61	4.76%	0.34%	48.7
SMA+vol	2.83	9168.4%	351.9%	32.91%	10.69	98	300	1.39	0.48	4.73%	0.18%	42.3

Figure 37: Backtests of different simple moving average signals for the short-part together with L7 as the long-part of the strategy.

Long-Short Backtests, Price Channel, In-Sample Data: April 1st 2015 – April 1st 2018												
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Longs	Number Shorts	Win/Loss Long	Win/Loss Short	Mean Ret Long	Mean Ret Short	Av. Hold Bar
PC	3.12	16474.2%	448.5%	25.90%	17.31	101	176	1.52	0.57	4.77%	0.55%	63.4
PC+BBW	2.86	7681.8%	326.4%	24.52%	13.31	101	99	1.52	0.5	4.77%	0.13%	72.6
PC+vol	3.31	19228.3%	477.3%	23.61%	20.21	101	126	1.52	0.66	4.77%	0.84%	69.7

Figure 38: Backtests of different price channel signals for the short-part together with L7 as the long-part of the strategy.

Long-Short Backtests, Bollinger Bands, In-Sample Data: April 1st 2015 – April 1st 2018												
Strategy	Sharpe Ratio	Return	Annual Return	Maximum Drawdown	MAR Ratio	Number Longs	Number Shorts	Win/Loss Long	Win/Loss Short	Mean Ret Long	Mean Ret Short	Av. Hold Bar
BB	2.54	7218.1%	317.7%	34.97%	9.09	101	203	1.52	0.46	4.28%	0.1%	67.4
BB+BBW	2.75	8467.6%	340.3%	35.02%	9.72	101	109	1.52	0.63	4.77%	0.27%	78.1
BB+vol	2.88	11988.1%	393.7%	30.41%	12.95	101	166	1.52	0.51	4.77%	0.4%	70.5
BB+HH+vol	3.38	23409.0%	516.2%	23.84%	21.65	101	188	1.52	0.47	4.77%	0.7%	60.2

Figure 39: Backtests of different Bollinger bands signals for the short-part together with L7 as the long-part of the strategy.