Master's Thesis Quantitative Finance

Erasmus School of Economics

(FEM21030)

*Joris Bakker (435108)*

# Technical Analysis in the Cryptocurrency Market

*Assessment of intra-day trading strategies in the BitCoin market based on multiple data-snooping tests*

**Abstract**

This paper examines the profitability and significance of a universe of 3312 intra-day technical trading rules on the 5-minute BTC/USD spot exchange rate between January 2013 and July 2017. We find numerous significantly profitable trading strategies, even after adjusting for data-snooping effects and transaction costs. However, profitability is highly unstable and declines over time. Combining signals of multiple trading rules by means of a neural network classification algorithm results in strategies which outperform the individual trading rules and benchmarks based on risk-adjusted profitability and break-even transaction costs. It is concluded that technical analysis in the cryptocurrency market is significantly profitable and that the cryptocurrency market is not fully efficient.
**Keywords:** *Technical Trading Rules, Data-snooping, Cryptocurrencies, High-frequency Trading, Foreign Exchange Market, Neural Networks*

supervised by

Dr. D. van Dijk

X. Gong

A. Tilgenkamp

December 14, 2017

# Contents

# 1 Introduction

The use of technical analysis is a widespread and persistent phenomenon which is highly influential in the decision making of foreign exchange professionals. Trading rules based on technical analysis have proved to be capable of providing valuable economic signals and to provide attractive returns. While numerous studies have been conducted on the profitability of technical trading rules in the equity and foreign exchange market, the cryptocurrency market has never been directly addressed. The main contribution of this paper is to extend the research on technical trading rules by evaluating a large universe of intra-day trading strategies in the cryptocurrency market. We find numerous significantly profitable strategies, even after adjusting for data-snooping effects and transaction costs.

The continued use and profitability of technical analysis is puzzling (Taylor & Allen 1992). Technical analysis involves the prediction of future exchange rate movements from an inductive analysis of historical time series using quantitative techniques. Technical analysis is not rooted in underlying financial theory, but relies solely on recurring past exchange rate patterns. As, according to the efficient market hypothesis (Fama 1970), past information should already be embodied in current prices, persistent performance of technical trading rules is surprising. Particularly in the foreign exchange and cryptocurrency markets, which are characterized by large trading volumes and almost non-existent private information about fundamentals, technical trading rules should not yield persistent excess returns. Finding profitable technical trading rules in the cryptocurrency market would provide empirical evidence against market efficiency.

Technical analysis is widespread and primarily adopted for short trading horizons. Menkhoff & Taylor (2007) introduce two stylized facts regarding the *prevalence* of technical analysis in the foreign exchange market[1]:

1. *"Almost all foreign exchange professionals use technical analysis as a tool in decision making at least to some degree".* (p. 940)

2. *"The relative weight given to technical analysis as opposed to fundamental analysis rises as the trading or forecast horizon declines."* (p. 940)

The intensive use of technical analysis for short trading horizons contradicts the efficient market hypothesis and requires some further review. Menkhoff & Taylor (2007) argue that there prevails a consensus that fundamentals are able to explain long-term exchange rate behavior, but a fundamentals-based model for exchange rate movements in the short-term is still not widely accepted. Neely & Weller (1999) showed, among others, that in the short-term, the performance of technical trading rules is considerably better than forecasts based on macroeconomic information. Schulmeister (2009) shows that the profitability of some technical models have declined substantially since the 1960s and have been unprofitable since the 1990s, when based on daily data. However, when based on 30-minute time intervals, the same models generate substantial returns which do not seem to decline over time. In a more recent study, Manahov et al. (2014) argue that nearly all foreign exchange traders who use technical analysis operate at a high-frequency level and that over 75% of all foreign exchange trades take place within a single day. The large weight on technical analysis for short-term trading is caused by the incapability of explaining short-term price movements by fundamentals.

[1] Based on (survey) studies by Taylor & Allen (1992), Menkhoff (1997), Lui & Mole (1998), Cheung & Wong (2000), Oberlechner (2001), Cheung & Chinn (2001), Cheung et al. (2004) and Gehrig & Menkhoff (2004)

Technical analysis can be profitable in the foreign exchange market. Menkhoff & Taylor (2007) introduce three stylized facts regarding the *profitability* of technical trading rules in the foreign exchange market. The first stylized fact is given by[2]:

3. *"The consideration of transaction costs and interest rate costs actually faced by professionals does not necessarily eliminate the profitability of technical currency analysis".* (p. 946)

This insight is important but evident; if technical analysis was never profitable, it's widespread application was ambiguous. Nevertheless, academics seem to be skeptical about the profitability of technical trading rules. Olson (2004) showed that the out-of-sample profitability of simple moving average technical trading rules based on daily exchange rates declined over time, eliminating temporary risk-adjusted market inefficiencies. Neely et al. (2009) showed that daily returns tend to deteriorate over time as more traders learn about the technical trading rules and start to exploit them, but with a slower speed than consistent with market efficiency. Similarly, literature on *intra-day* technical trading rules does not convey a clear picture. Gençay et al. (2002) find that technical trading models with high-frequency data can generate excess returns, while Curcio et al. (1997) and Neely & Weller (2003) find no evidence of excess returns of the intra-day strategies. In this paper we consider actual transaction costs and thus provide a sound report regarding the excess profitability of technical trading rules in the cryptocurrency market.

Performance of technical analysis is volatile over time. The second[3] and third[4] stylized facts are given by:

4. *"Technical analysis tends to be more profitable with volatile currencies".* (p. 947)

5. *"The performance of technical trading rules is highly unstable over time".* (p. 947)

Cornell & Dietrich (1978) and Neely & Weller (1999) both show that the higher returns of volatile currencies are no compensation for bearing more systematic risk. Volatility causes more opportunities to improve upon the original price series. As cryptocurrencies appear to be more volatile than developed fiat currencies, this stylized fact is promising. Although instability of trading rule performance is undesired, fundamentals-based exchange rate models are also characterized by unstable performance (Menkhoff & Taylor 2007). In summary, technical analysis is widely used and can be profitable, particularly when trading horizons are short and prices are volatile. We show in this paper that the cryptocurrency market is consistent with all stylized facts on profitability of technical analysis in the foreign exchange market.

Data-snooping is a well-documented statistical issue which is often not correctly addressed when evaluating a variety of models. In their literature review, Park & Irwin (2007) acknowledge the potential profitability of technical trading rules, but state that most empirical studies fail to account for, among others, data-snooping. Data-snooping biases arise when academics continue to search for predictive trading rules, while only conducting individual tests using the same dataset. To test a large universe of technical trading rules correctly, all models should be tested together for their significance. Sullivan et al. (1999) were the first to account for data-snooping effects in testing a universe of trading

[2]Based on findings by Cornell & Dietrich (1978), Sweeney (1986), Schulmeister (1987), LeBaron (1999), Saacke (2002) and Neely et al. (2009)

[3]Based on empirical evidence presented in studies by Cornell & Dietrich (1978), Dooley & Schafer (1983), Lee & Mathur (1996) and Neely & Weller (1999)

[4]Based on works of Loque et al. (1978), Dooley & Schafer (1983), Menkhoff & Schlumberger (1995), LeBaron (2000), Dueker & Neely (2007) and Neely et al. (2009)

rules. We adopt four methods to make appropriate statistical inferences and account for data-snooping biases: White (2000)'s Reality Check, Hansen (2005)'s SPA test, Romano & Wolf (2005)'s studentized stepM test and Hsu et al. (2010)'s stepwise SPA test. This is the first study on technical analysis in the foreign exchange market which conducts and compares these four data-snooping methods on the same universe of trading rules.

A major contribution of this paper is the extension it provides to the research on technical trading rules to the *cryptocurrency market*. A cryptocurrency is a digital asset designed to work as medium of exchange, acting as an alternative to fiat currencies. Cryptocurrencies use encryption techniques to secure transactions and control the creation of additional units. While the idea of a digital currency is long-established, the development has gained traction as libertarian response to the perceived failures of governments and central banks during the 2008 crisis (Balcilar et al. 2017). The most prominent cryptocurrency is BitCoin. BitCoin is an open-source digital payment system, first described by Nakamoto (2009), that is powered by its users with no central authority. BitCoins are created in a process called 'mining', in which users provide computer power to validate and record BitCoin payments into a publicly distributed ledger called 'the blockchain'. Besides the generation of new BitCoins, miners can be rewarded by requiring transaction fees for their services, however this is optional. As a result, transaction fees are set by supply and demand; allowing higher transaction fees will increase the speed of your transaction as more miners are willing to provide their computer power. In fact, Nakamoto describes a 'fee market' that should gradually substitute the reward of new BitCoins to sustain a healthy mining industry. Some other major differences with fiat currencies include a fixed maximum supply of 21 million units, the absence of a related interest rate and no link to a geographical region. Dwyer (2015) provides an extensive overview of the principles behind BitCoin and other cryptocurrencies. Due to BitCoin's limited supply, mining costs (in the form of computer power) and absence of an interest rate, it has many similarities with precious metals.

Cryptocurrencies are perfectly suitable for high-frequency trading. Firstly, the speed of transactions is much higher compared to that of fiat currencies. Transactions will take less than 10 minutes, independent of the location of the wallets and the size of the transaction. Secondly, costs of transactions between cryptocurrency wallets are very low and independent of their size and location. The speed and costs of a transaction between cryptocurrencies and fiat currencies depend on the exchange, but are preferred over transactions between fiat currencies (Kim 2017). Moreover, the network is open 24-hours a day and does not bear transaction size restrictions. The combined market capitalization of all cryptocurrencies is rapidly increasing and currently exceeds USD 310 billion.[5] With a market capitalization of USD 168 billion, BitCoin is currently the largest cryptocurrency. Almost 80% of the BitCoin trades are driven by high-frequency traders (Chen et al. 2017).

Financial research on cryptocurrencies is limited and calls for extension. The academic literature on cryptocurrencies is primarily focused on the legal (Plassaras 2013) and ethical (Angel & McCabe 2015) aspect of digital currencies. Nevertheless, the attention for the financial and economical literature on cryptocurrencies is increasing. Balcilar et al. (2017) provide a brief overview on the literature regarding the financial and speculative characteristics of BitCoin. Polasik et al. (2015) show that the price of BitCoin is positively related with the number of Google searches and news articles related to BitCoin, which might support momentum trading strategies. Briere et al. (2015) show that BitCoin investments can dramatically improve the risk-return trade-off of well-diversified portfolios. Urquhart (2017) shows that the BitCoin market is not weakly efficient between August 2010 and July 2016. Balcilar et al. (2017) show that BitCoin volume can predict returns, which might

[5] https://coinmarketcap.com/ as of 28-11-2017

support technical trading rules based on volume. The increased academic attention for cryptocurrencies coincides with the increased awareness by central banks. According to Miller et al. (2017), China has announced trials of its own prototype cryptocurrency, being the first central bank issuing a digital currency. The ECB and the Bank of Japan have launched a study regarding the use of a distributed ledger and the Dutch central bank has even created its own digital currency in order to better understand the principles and potential use. As digital currencies receive more attention from academics and practitioners, a comprehensive study towards the profitability of technical analysis in the cryptocurrency market is needed.

The purpose of this paper is to examine whether technical analysis in the cryptocurrency market is significantly profitable and persistently exploitable. We examine a universe of 3312 technical trading rules on the 5-minute USD/BTC spot exchange rate between January 2013 and July 2017. To the best of our knowledge, this paper is the first which evaluates a universe of trading rules on the BitCoin price movement. Both the stepM test and SSPA test report numerous trading rules which significantly outperform the buy-and-hold benchmark. Moreover, the presence of transaction costs does not necessarily eliminate profitability. White's Reality Check and the SPA test reveal that the strategy with the best performance is highly significant. Nonetheless, profitability appears to decline over time, which may serve as evidence for increased efficiency of the cryptocurrency market. Consistent with the stylized facts mentioned above, returns are unstable over time and higher during more volatile periods. Although profitable trading strategies are identified, individual trading rules used in isolation can not be expected to predict all price movements. To determine whether combining information of multiple trading strategies outperforms individual trading rules, a neural network classification algorithm is trained to combine trading signals. The resulting combined strategies outperform the individual trading rules based on return, Sharpe ratio and break-even transaction costs. Hence, it is concluded that technical analysis in the cryptocurrency market is significantly profitable and exploitable. The findings of this study are relevant for all traders, regulators and academics involved in the cryptocurrency market.

The remainder of this paper proceeds as follows. Section 2 specifies the universe of technical trading rules considered in this study. In section 3 we describe the data and provide descriptive statistics. Section 4 introduces the performance metrics used to assess the performance of the trading strategies. Section 5 provides an overview of the applied methods to mitigate data-snooping effects. In section 6 we report the main empirical results. Section 7 introduces neural networks and provides the results on combining individual trading rules. Sections 8 and 9 conclude, discuss the paper and provide recommendations for further research.

## 2 Universe of Technical Trading Rules

The tested universe of technical trading rules consists of 3312 strategies. We include seven classes of trading rules, including trend-following and trend-reversal strategies. Since the data-snooping correction is only relative to the set of evaluated strategies, the design of the trading rule universe is important. This section specifies the universe of technical trading rules and clarifies the rationale behind all the strategies.

The design of the universe of trading rules is important. As mentioned by Sullivan et al. (1999), outperforming trading rules only have consequences for market efficiency when the trading rules were known during the sample period. Therefore, all classes of trading rules under consideration are drawn from academic literature published before the start of the sample period. As described by Sullivan et al. (2001), two errors, over-searching and under-searching, can occur in specifying the universe of trading rules. First, as result of the survivorship bias, we may have neglected unsuccessful trading rules that were filtered out of the recent literature through the sequence of studies focusing on successful strategies. Inference based solely on the set of successful and surviving strategies is misleading, as these strategies are drawn from a larger universe. The data-snooping adjustment would not account for the full set of trading rules and the estimated $p$-values of the best-performing rules would be biased towards zero. Secondly, we may have included strategies that were never considered by investors, reducing the power of the data-snooping tests. Fortunately, Sullivan et al. (2001) present a heuristic argument why addition of uninformative rules will not lead to large changes in $p$-values once the universe is large.[6] To circumvent both concerns, we select a large variety of trading rules and parameterizations which is consistent with the literature.

Investors' reaction to past performance depends on their believe in momentum. Investors believing in momentum adopt *trend-following* trading rules which generate signals in the same direction as the price deviation from the current state. These investors expect that trends will continue in the same direction as the previous movement. Investors adopting *trend-reversal* strategies believe that price deviations from the current state are temporary and that the price will return to its original state. Hence, trend-reversal strategies generate signals in opposite direction as the price deviation from the original state. Trend-following and trend-reversal strategies are both well-documented and supported by academic literature, see e.g. Menkhoff & Taylor (2007) and Menkhoff et al. (2012). The performance of momentum strategies primarily depends the trading horizon (Jegadeesh & Titman 1993) and region (Fama & French 2012). As this is the first paper evaluating technical trading rules in the BitCoin market, we test both schools of thought. Therefore, and in line with Hsu & Kuan (2005) and Chicaroli & Pereira (2015), we include the contrarian version of most strategies in the universe of trading rules.[7]

We employ seven classes of technical trading rules. The filter, moving average, support and resistance, channel breakout, and oscillator trading rules aim to exploit trends in *prices*. These five classes of trading rules have been widely used by foreign exchange market professionals and have been studied extensively by academics.[8] The remaining two classes of trading rules, on-balance volume averages and bollinger bands, are based on volume and price volatility, respectively. The full universe of the $K = 3312$ trading rules is given in table 1. Each trading rule $k \in K$ generates trading signals, produced and executed at time $t$, resulting in positions $s_{k,t}$. The trading positions equal 1 for a long position and $-1$ for a short position, it is not possible to take a neutral position. If no trading signal is generated, or if the same signal compared to time $t-1$ is generated, the current position is maintained.[9] Note that taking opposite positions compared to $s_{k,t}$ is transforming the trading rule from a trend-following to a trend-reversal strategy, or vice versa. In this manner we included the contrarian version of most strategies in the universe.

[6]Moreover, the SPA test answers this concern by excluding the performance metrics of uninformative strategies when testing for trading rule significance, see section 5.

[7]Inclusion of contrarian strategies for which no reasonable rationale exists would result in over-searching and are therefore excluded from the universe.

[8]See Sweeney (1986), Schulmeister (1987), Brock et al. (1992), Levich & Thomas (1993), Neely (1997), LeBaron (1999), Sullivan et al. (1999), Qi & Wu (2006), Schulmeister (2009) and Hsu et al. (2016)

[9]We would like to make a clear distinction between what we call trading *signals* and *positions*. Trading signals can be long (1), hold (0) and short (-1) and trigger the trading positions $s_{k,t}$. Trading positions can only be long (1) and short (-1). For example, a long (1) signal is generated, but thereafter all signals are hold (0) signals. As the investor will have a long position during his complete trading period, the resulting position vector consists of ones only. The resulting signal vector is a zero vector with a 1 as first element.

All trading rules make use of threshold parameters to separate weak signals from stronger signals. The parameterizations of the trading rules are given in table 17 in the appendix. The classes of trading rules are explained in more detail below.

**Table 1:** Full universe of technical trading rules

| Class of trading rule | Number of parameterizations |
|---|---|
| Standard strategies | 225 |
| Filter | 225 |
| Moving average | 396 |
| Support and resistance | 270 |
| Channel breakout | 360 |
| On-balance volume average | 495 |
| Bollinger bands | 180 |
| | 2106 |
| Contrarian strategies | |
| Moving average | 396 |
| Support and resistance | 270 |
| Channel breakout | 360 |
| Bollinger bands | 180 |
| | 1206 |
| Total | 3312 |

*The full universe of technical trading rules and the number of parameterizations within each class of trading rules. The contrarian rules generate the exact opposite trading positions compared to their standard counterpart.*

**Filter rules** attempt to follow trends by buying (selling) a currency whenever it has risen (fallen) by a given percentage after the most recent low (peak). Filter rules were first proposed by Alexander (1961) and tested extensively by academics thereafter, of which Fama & Blume (1966) and Sweeney (1988) are the most prominent. A filter rule is specified as follows. If the price of the foreign currency (BitCoin) exceeds its most recent low by a predefined threshold of $x\%$, borrow the local currency (dollar) and buy the foreign currency. When the price of the foreign currency moves down at least $x\%$ from a subsequent high, short sell the foreign currency and buy the local currency with the proceeds. The position is maintained until the price of the foreign currency exceeds its most recent low by $x\%$ again, after which the above mentioned strategy is repeated. Such a $x\%$ filter rule may be expressed as (Menkhoff & Taylor 2007):

$$s_{k,t} \begin{cases} 1 & \text{if} \quad \dfrac{p_t - \left\{p_{t-i} | i = \min[i > 0 | (p_{t-i} - p_t) < 0 \wedge (p_{t-i} - p_{t-i-1}) < 0]\right\}}{\left\{p_{t-i} | i = \min[i > 0 | (p_{t-i} - p_t) < 0 \wedge (p_{t-i} - p_{t-i-1}) < 0]\right\}} > x \\ -1 & \text{if} \quad \dfrac{\left\{p_{t-i} | i = \min[i > 0 | (p_{t-i} - p_t) > 0 \wedge (p_{t-i} - p_{t-i-1}) > 0]\right\} - p_t}{\left\{p_{t-i} | i = \min[i > 0 | (p_{t-i} - p_t) > 0 \wedge (p_{t-i} - p_{t-i-1}) > 0]\right\}} > x \\ s_{k,t-1} & \text{else} \end{cases}$$

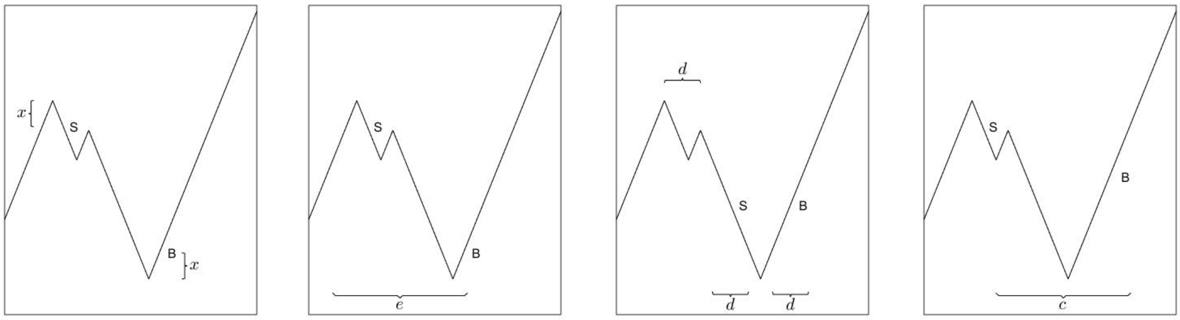
where $p_t$ is the price (exchange rate) of the foreign currency at time $t$ and where $i \in \mathbb{Z}$. Moreover, following Sullivan et al. (1999), three variations are considered:

1. Redefining the most recent high (low) as the highest (lowest) price over the $e$ most recent time intervals,
2. Requiring the buy or sell signal to remain valid for a predefined number of time intervals $d$ before a trade is executed,
3. Holding a given position for at least a predefined number of time intervals $c$, ignoring all generated signals.

The rationale behind defining alternative extrema is to neglect the 'noise' of recent small price movements when past highs or lows are more informative. In this manner, only large deviations will generate trading signals. The rationale behind both the time delay and holding period is to disregard the noise of frequent price fluctuations in order to find a better balance between capturing all price trends and reduction of the number of trades (transaction costs). Implementation of the time delay period aims to detect structural trends and to neglect single movements, separating temporary from persistent signals. A holding period assures that signals immediately after a trade are ignored and aims to exploit longer trends. Note that during the holding period, the ignored signals can act as the required signals to meet the time delay period for a potential next trade. As a result, if both the delay filter and holding period are active, an opposite trade can occur immediately after a holding period. In the remainder of the paper, an $x\%$ filter rule with alternative extrema of length $e$, a delay filter of length $d$ and a holding period of length $c$ is defined as $F(x, e, d, c)$. Since the filter rules generate trade signals in the same direction as the last price deviation, the filter rules are classified as trend-following. Trend-reversal filter rules are not described in the literature and a reasonable rationale for such rules is not reported. Therefore, trend-reversal filter rules are not included in the set of contrarian strategies.

Figure 1 clarifies the different variations by illustrating the trading positions of the filter rules. This paragraph explains the figures in more detail. Figure 1a demonstrates a basic $x\%$ filter rule with none of the variations applied. A sell signal is generated and executed when the price has fallen by $x\%$ after the first peak, indicated with an 'S' in the graph. The price increase after the first local minimum does not generate a buy signal as the increase does not exceed $x\%$. The price decrease after the second local maximum generates a sell signal, however the trade is not executed as the investor already has a short position at the time of the signal. When the price has increased over $x\%$ after the second local minimum a buy signal is generated and executed, indicated with a 'B' in the graph. Figure 1b demonstrates the trade signals of a filter rule for which the high and lows are redefined as the extrema over the $e$ most recent time intervals. For the price movement given in the figure, the buy and sell signals are equal to that of the basic filter rule. Both the buy and sell signal remain valid as the first peak and the second low are both the extrema when considering the $e$ most recent time intervals. Figure 1c demonstrates the trade signals of a filter rule with a delay filter of length $d$. As the sell signal after the first peak does not remain valid for at least $d$ periods, no trade is executed. The sell signal after the second peak remains valid for at least $d$ periods and a short position is taken at the time indicated with an 'S' in the graph. Similarly, $d$ periods after the second local minimum, a buy signal is generated and executed. Figure 1d demonstrates the trade signals of a filter rule with a holding period. After the short position is taken at the time indicated with an 'S' in the graph, a holding period of length $c$ is active in which all buy and sell signals are ignored. When the holding period has ended, a buy signal is generated and executed, indicated with a 'B' in the graph.

**Figure 1:** Signal generation a filter trading rule and its variations




**(a)** $F(x, -, 0, 0)$ **(b)** $F(x, -, 0, 0)$ **(c)** $F(x, -, 3, 0)$ **(d)** $F(x, -, 0, 6)$

*These figures present the trade positions $s_{k,t}$ of the filter rule and its variations. The line represents the price movement of the foreign currency $p_t$. A 'B' indicates a buy signal (long position) and an 'S' a sell signal (short position). In this example, the investor starts with a long position in the foreign currency. Figures 1b, 1c and 1d present the trading signals of filter rule with redefined extrema, a delay filter or a holding period as described above.*

**Moving average rules** attempt to follow trends and identify imminent trend breaks. Unlike filter rules, moving average trading rules aim to smooth out volatile time series. The use of moving averages in trading rules was first described by Gartley (1935) and tested extensively thereafter, e.g. Brock et al. (1992). In a more recent study, Schulmeister (2009) provides evidence that moving average rules in the stock market are only profitable when adopting an intra-day trading frequency. Hsu et al. (2016) report excess returns in the foreign exchange market when using moving average rules on daily data, while Frömmel & Lampaert (2016) find significant profits using 10 to 60-minute returns. Many different types of moving average rules are used by practitioners and academics, but, following Sullivan et al. (1999), we only examine double moving average rules.

Double (cross-over) moving average rules consist of one short-term and one long-term single moving average. Let the single moving average over $j$ time intervals at time $t$ be defined as

$$MA_t(j) = \frac{1}{j} \sum_{i=0}^{j-1} p_{t-i}, \tag{2.1}$$

where $j, i \in \mathbb{Z}$. Double moving average rules are specified as follows. Let $q < j$. If $MA_t(q)$ exceeds $MA_t(j)$ more than $b$%, borrow the local currency and buy the foreign currency. When $MA_t(q)$ falls below $MA_t(j)$ more than $b$%, short sell the foreign currency and buy the local currency. Thus, a strong upward (downward) penetration of the long-term moving average by the short-term moving average is regarded as the initiation of an upward (downward) trend and hence a buy (sell) signal is generated. Figure 2a clarifies the buy and sell signals of the double moving average rule for $q = 3$ and $j = 5$. Such a double moving average trading rule may be expressed as (Menkhoff & Taylor 2007):

$$s_{k,t} \begin{cases} 1 & \text{if} \quad MA_t(q) > (1+b)MA_t(j) & (2.2) \\ -1 & \text{if} \quad MA_t(q) < (1-b)MA_t(j) & (2.3) \\ s_{k,t-1} & \text{else} \end{cases}$$

with $q < j$. In line with Sullivan et al. (1999), we impose a time delay period of length $d$ and holding period of length $c$ on the moving average rules. In the remainder of the paper, a double moving average rule with a short moving average of length $q$, a long moving average of length $j$, a threshold of $b\%$, a delay filter of length $d$ and a holding period of length $c$ is defined as $MA(q, j, b, d, c)$. The complexity of moving average rules can be intensified easily, e.g. analyzing the slope of the penetration or imposing exponential moving averages, but this paper only considers the basic and most widely used rules.

The double moving average trading rules as defined above are trend-following strategies: when prices strongly increase (decrease), a long (short) position is taken. Although most literature specifies moving average rules as trend-following, trend-reversal moving average rules are studied as well. For example, Balsara et al. (2009) find that contrarian double moving average rules generate excess returns in the US stock market, while trend-following double moving average rules under-perform the buy-and-hold benchmark. The rationale behind a contrarian double moving average rule is that any deviation from the long-term moving average is temporary and likely to be followed by a reversion in price (mean-reversion). In the remainder of the paper, a contrarian double moving average rule is denoted as $MA^c(q, j, b, d, c)$.

**Support and resistance rules** attempt to identify levels below (above) which the price $p_t$ appears to have difficulty falling (rising). These levels are called the support and resistance level, respectively, and are often defined as the local minimum and maximum. The rationale behind support and resistance levels is that investors aim to sell (buy) at a peak (low), which will cause resistance to a price rise (drop) above (below) a previous peak (low). A breakout through the support (resistance) level is considered as a trigger for further price movements in the same direction, hence a trend-following sell (buy) signal is generated. Support and resistance rules are initially described by Wyckoff (1910) and tested intensively thereafter, e.g. Brock et al. (1992) report excess returns by using support and resistance rules on daily data in the equity market.

The support and resistance rules are specified as follows. If the price of the foreign currency exceeds the maximum price over the previous $n$ time intervals at least with $b\%$, borrow the local currency and buy the foreign currency. When the price of the foreign currency drops below the minimum price over the previous $n$ time intervals at least with $b\%$, short sell the foreign currency and buy the local currency. A support and resistance trading strategy may be expressed as:

$$s_{k,t} \begin{cases} 1 & \text{if} \quad p_t > (1+b)\max(\{p_{t-i}\}_{i=1}^{n}) & (2.4) \\ -1 & \text{if} \quad p_t < (1-b)\min(\{p_{t-i}\}_{i=1}^{n}) & (2.5) \\ s_{k,t-1} & \text{else} \end{cases}$$

for $n \in \mathbb{Z}$. Figure 2b illustrates the trading positions of a trading rule with a support (resistance) level of the minimum (maximum) over the previous $n = 5$ time intervals. Similar as before, we impose a time delay filter and holding period. In the remainder of the paper, a support and resistance rule evaluated over $n$ periods, with a threshold of $b\%$, a delay filter of length $d$ and a holding period of length $c$ is defined as $SR(n, b, d, c)$.

The support and resistance rules as defined above are trend-following strategies. Nonetheless, Osler (2000) studied support and resistance trading rules on 1-minute exchange rate data and finds significant evidence of predictive power regarding trend-reversal support and resistance rules. The rationale behind a contrarian support and resistance rule is that any breakout through the support and resistance level indicates that the currency is mispriced and is likely to be followed by a reversion in price. Although contrarian support and resistance rules may be interpreted as similar to filter rules, there is a difference. Filter rules generate a trend-following signal after falling below a maximum, while contrarian support and resistance rules generate a trend-reversal signal after exceeding a maximum. In the remainder of the paper, a contrarian support and resistance rule is denoted as $SR^c(n, b, d, c)$.

**Channel breakouts** occur when the price moves outside the boundaries of a channel defined by the minimum and maximum over the previous $n$ time intervals. A channel *only* occurs when the maximum of the previous $n$ time intervals is within $x\%$ of the minimum of the previous $n$ time intervals, excluding the current price. Similar breakout channels were first described by Donchian (1960). Hsu et al. (2016) show that channel breakout strategies on daily data can be profitable in the foreign exchange market.

The channel breakout strategies are specified as follows. If the price of the foreign currency penetrates the upper bound, a buy signal is generated. When the price penetrates the lower bound, a sell signal is generated. A channel breakout trading rule may be expressed as:

$$s_{k,t} \begin{cases} 1 & \text{if} \quad p_t > \max(\{p_{t-i}\}_{i=1}^n) \wedge \dfrac{\max(\{p_{t-i}\}_{i=1}^n)}{\min(\{p_{t-i}\}_{i=1}^n)} < (1+x) & (2.6) \\ -1 & \text{if} \quad p_t < \min(\{p_{t-i}\}_{i=1}^n) \wedge \dfrac{\max(\{p_{t-i}\}_{i=1}^n)}{\min(\{p_{t-i}\}_{i=1}^n)} < (1+x) & (2.7) \\ s_{k,t-1} & \text{else} \end{cases}$$

for $n \in \mathbb{Z}$. Figure 2c illustrates the buy and sell signals of a channel breakout strategy evaluated over $n = 5$ time intervals. Similar as above, we include a percentage band $b$ and a holding period of length $c$. We exclude a delay period $d$ since it is unlikely that after a trade signal a new channel occurs. In the remainder of the paper, a channel breakout rule evaluated over $n$ time intervals, with a threshold of $x\%$, a percentage band $b$ and holding period of length $c$ is defined as $CB(n, x, b, c)$.

The channel breakout rules as defined above are trend-following strategies. Nonetheless, Balsara et al. (2009) report profitable trend-reversal channel breakout strategies. Similar as compared to contrarian support and resistance rules, the rationale behind contrarian channel breakout strategies is that breakouts might indicate mispricing of the currency. Contrarians might believe that the intrinsic value of the asset lies within the boundaries of the channel and that deviations are temporary. In the remainder of the paper, a contrarian channel breakout rule is denoted as $CB^c(n, x, b, c)$.

**Oscillator trading rules** are designed to detect price movements that have been too rapid and for which a correction is imminent. A widely used form is the relative strength indicator (Levy (1967), Wilder (1978)). The relative strength indicator (RSI) measures the strength of price increases relative to the strength of price decreases over a fixed period. The indicator may be expressed as (Menkhoff & Taylor 2007):

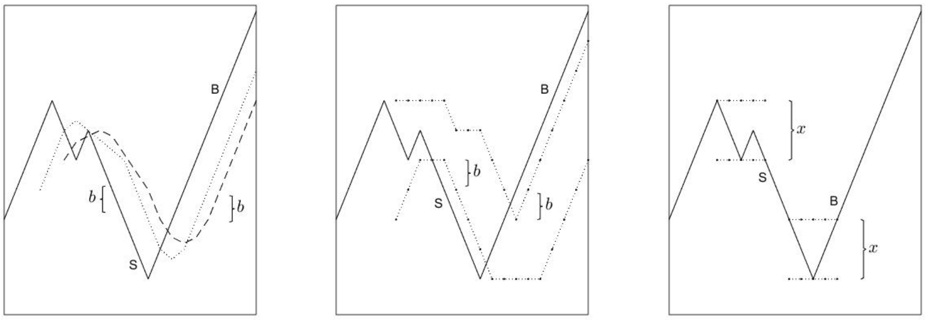
$$RSI_t = 100 \frac{U_t}{U_t - D_t} \tag{2.8}$$

where

$$U_t = \sum_{i=0}^{m-1} (p_{t-i} - p_{t-i-1}) \mathbb{1}_{p_{t-i} - p_{t-i-1} > 0}, \tag{2.9}$$

$$D_t = \sum_{i=0}^{m-1} |p_{t-i} - p_{t-i-1}| \mathbb{1}_{p_{t-i} - p_{t-i-1} < 0} \tag{2.10}$$

**Figure 2:** Signal generation of moving average, support & resistance and channel breakout trading rules




**(a)** $MA(5, 3, b, 0, 0)$ **(b)** $SR(5, b, 0, 0)$ **(c)** $CB(5, x, 0, 0)$

*Figure 2a presents the trade positions $s_{k,t}$ of the double moving average rule. The dashed line represents $MA_t(5)$ and the dotted line $MA_t(3)$. Figure 2b illustrates the trade positions of a strategy with a support (resistance) level of the minimum (maximum) over the previous $n = 5$ time intervals. The dash-dot lines display the support and resistance levels. Figure 2c presents the trading positions of a channel breakout rule evaluated over $n = 5$ time intervals. The solid line represents the price movement of the foreign currency $p_t$. A 'B' indicates a buy signal (long position) and an 'S' a sell signal (short position). In this example, the investor starts with a long position in the foreign currency.*

and where $m \in \mathbb{Z}$ denotes the number of time intervals under consideration. The trading rule used in this study is specified as follows. If the relative strength indicator exceeds $50 + v$ for at least $d$ time periods, the foreign currency is considered overbought and a sell signal is generated. If the RSI drops below $50 - v$ for at least $d$ time periods, the foreign currency is considered oversold and a buy signal is generated. The RSI trading rule may be expressed as:

$$s_{k,t} \begin{cases} 1 & \text{if} \quad RSI_t < 50 - v \qquad (2.11) \\ -1 & \text{if} \quad RSI_t > 50 + v \qquad (2.12) \\ s_{k,t-1} & \text{else} \end{cases}$$

Common values of the indicator used to detect overbought or oversold signals are 70 and 30, respectively. Figure 3a illustrates the positions of a RSI trading rule with $m = 5$. Similar as above, a time delay filter and holding period are included. In the remainder of the paper, RSI trading rule evaluated over $m$ time intervals, with a threshold of $v$, a delay filter of length $d$ and a holding period of length $c$ is defined as $RSI(m, v, d, c)$.

The RSI trading rules are trend-reversal trading rules. As the literature does not cover trend-following RSI trading rules, inclusion of these rules would result in over-searching. Hence, trend-following RSI strategies are not included in the universe of trading rules.

**On-balance volume average rules** include information on traded volume in the determination of trading positions. The on-balance volume average is introduced by Gartley (1935) and popularized by Granville (1963). The on-balance volume indicator is constructed by taking the cumulative sum of volumes from time intervals in which the price increases and subtracting the cumulative sum of volumes from time intervals in which the price decreases. In this manner, the trading rule is able to separate high volume signals from the weaker low volume signals. The rationale behind the on-balance volume indicator is that volume eventually drives prices, even if the magnitude of the price movements is minimal. To generate trading signals, the moving average rules introduced above are applied to the on-balance volume indicator. The on-balance volume indicator is defined as:

$$OBV_t = \sum_{i=0}^{t} v_i(\mathbb{1}_{p_i > p_{i-1}} - \mathbb{1}_{p_i \leq p_{i-1}}) \tag{2.13}$$

where $v_t$ is the traded volume between time $t-1$ till $t$. The on-balance volume moving average $MA_t^{OBV}(j)$ is defined as:

$$MA_t^{OBV}(j) = \frac{1}{j}\sum_{i=0}^{j-1} OBV_{t-i}. \tag{2.14}$$

Then, the trading positions are generated by:

$$s_{k,t} \begin{cases} 1 & \text{if} \quad MA_t^{OBV}(q) > (1+b)MA_t^{OBV}(j) & (2.15) \\ -1 & \text{if} \quad MA_t^{OBV}(q) \leq (1-b)MA_t^{OBV}(j) & (2.16) \\ s_{k,t-1} & \text{else} \end{cases}$$

with $q < j$ and $b$ is a percentage band filter. Figure 3b illustrates the trading positions of a general on-balance volume moving average trading rule, with $q = 3$ and $j = 5$. Similar as above, we include a time delay filter $d$ and holding period $c$. In the remainder of the paper, on-balance volume average trading rules with a short moving average of length $q$, a long moving average of length $j$, a threshold of $b$%, a delay filter of length $d$ and a holding period of length $c$ is defined as $OBV(q, j, b, d, c)$.

The on-balance volume average trading rules are trend-following trading rules. As the literature does not cover trend-reversal on-balance volume average trading rules, inclusion of these rules would result in over-searching. Hence, trend-reversal on-balance volume strategies are not included in the universe of trading rules.

**Bollinger band rules** incorporate information on price volatility in the generation of trading signals. Bollinger bands are developed by Bollinger (1992) and widely used to determine whether prices are relatively high or low. Coakley et al. (2016) show that bollinger band trading rules remain robustly profitable across 22 daily exchange rates after mitigating data-snooping effects. The bollinger band indicator consists of three bands: a simple moving average as a measure of the price trend and an upper and lower band determined by price volatility. The moving average is defined as in (2.1). The standard deviation at time $t$ over the previous $j$ time intervals is defined as:

$$\sigma_t(j) = \sqrt{\frac{1}{j}\sum_{i=0}^{j-1}\Big(p_{t-i} - \bar{p}_t(j)\Big)^2} \tag{2.17}$$

where

$$\bar{p}_t(j) = \frac{1}{j}\sum_{i=0}^{j-1} p_{t-i}. \tag{2.18}$$

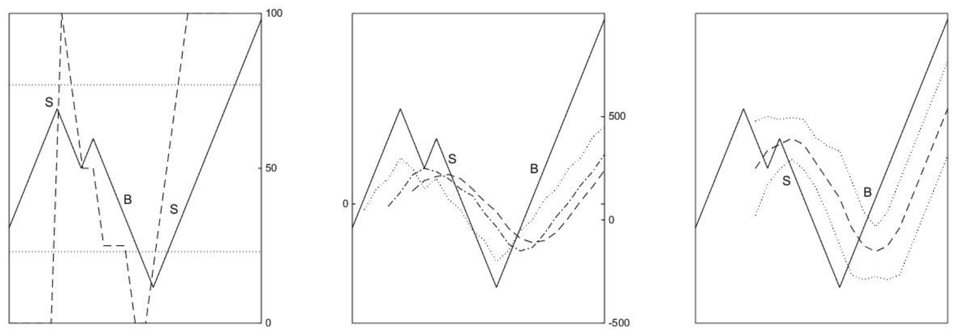
The upper and lower band are then defined as $k$ standard deviations above and below the moving average. In statistical terms, for $k = 2$, around 95% of the price movements should be contained in the band. The trading positions are generated by:

$$s_{k,t} \begin{cases} 1 & \text{if} \quad p_t < MA_t(j) - k\sigma_t(j) \quad (2.19) \\ -1 & \text{if} \quad p_t > MA_t(j) + k\sigma_t(j) \quad (2.20) \\ s_{k,t-1} & \text{else} \end{cases}$$

Similar as above, we include a time delay filter and holding period. In the remainder of the paper, bollinger band trading rules with a moving average of length $j$, a bandwidth of $k$ standard deviations, a delay filter of length $d$ and a holding period of length $c$ is defined as $BB(j, k, d, c)$. Figure 3c clarifies the trading signals of a bollinger band trading rule with $j = 5$ and $k = 1$.

The bollinger band strategies as defined above are trend-reversal trading rules. Nonetheless, Zarrabi et al. (2017) finds profitable trend-following bollinger band trading rules in the foreign exchange market between 1994 and 2012. Similar as compared to the trend-following support and resistance trading rules, the rationale behind trend-following bollinger band rules is that a breakout through the bands is considered as a trigger for further price movements in the same direction. Large price deviations relative to low volatility are then considered as structural breaks in price. In the remainder of the paper, a contrarian bollinger band rule is denoted as $BB^c(j, k, d, c)$.

**Figure 3:** Signal generation of RSI, on-balance volume average and bollinger band trading rules




**(a)** $RSI(5, v, 0, 0)$ **(b)** $OBV(5, 3, b, 0, 0)$ **(c)** $BB(5, 1, 0, 0)$

*Figure 3a presents the trading positions $s_{k,t}$ of the RSI trading rule with $m = 5$. The dashed line represents the RSI indicator and the dotted lines the overbought and oversold boundaries, all plotted on the right y-axis. Figure 3b present the trading signals of the on-balance volume moving average trading rule with $q = 3$ and $j = 5$. The dotted line represents the OBV indicator, the dashed line the long moving average and the dash-dot line the short moving average, all plotted on the right y-axis. Figure 3c presents the trading positions of the bollinger band rules. The dashed lines represents a moving average with $j = 5$ and the dotted lines the corresponding standard deviations, with $k = 1$. The solid line represents the price movement of the foreign currency. B indicates a buy signal (long position) and S a sell signal (short position). In this example, the investor starts with a long position in the foreign currency.*

# 3 Data

The dataset consists of the USD/BTC spot exchange rate between 01-01-2013 and 17-07-2017. Raw transaction data from the Bitstamp exchange is converted to 5-minute intervals in order to calculate returns with respect to closing prices. This section provides descriptive statistics and analyses of the dataset and returns.

The raw tick-by-tick data is collected from Bitcoincharts.com[10] and ranges from 03-09-2011 to 17-07-17. The dataset consists of transaction prices, volume and unix time rounded to the nearest second of all trades on the Bitstamp exchange. We selected the Bitstamp exchange due to its size[11], liquidity and safety (Bouri et al. 2017). The tick-data is re-sampled at 5-minute time intervals to calculate closing prices and returns.[12] Before 2013, the BitCoin was characterized by low trading volume and extreme volatility, see table 19 in the appendix. As the current BitCoin market is more mature, more liquid and practically a different industry compared to before 2013, we exclude these years from our analysis. As we conduct methods to mitigate data-snooping effects and we do not estimate any parameters, it is not necessary to perform out-of-sample tests. Hence, the full sample period ranges from 01-01-2013 to 17-07-2017.

Table 2 provides descriptive statistics regarding traded volume, prices and log returns. Figures 4a, 4b and 4c display the evolution of volume, price and returns over time. The BitCoin has appreciated drastically against the dollar, from USD 12.8 in 2013 to USD 2980 in 2017. The log returns are highly volatile and positively skewed. Interestingly, when evaluating the log returns on an hourly basis, the skewness is negative. Apparently, the number of extreme positive events is larger compared to extreme negative events, while the impact of the negative events is larger. The returns are strongly leptokurtic distributed, indicating relatively many extreme deviations from the mean. The non-normality of the returns is confirmed by a Jarque-Bera test. According to the Augmented Dickey Fuller unit-root test, the returns are stationary. The Ljung-box Q-test indicates significant autocorrelation in the returns. Compared to the summary statistics of the 5-min exchange rate of the USD against the EUR, GBP, JPY, AUD, CAD, reported in Kleinbrod & Li (2017), the coefficients of variation are comparable. The extreme excess kurtosis is the main difference between the BTC/USD and the fiat currency exchange rates.

Figure 5a and 5b illustrate the intra-day traded volume and volatility pattern, where volatility is measured as absolute return. The investor base of the USD/BTC trades on Bitstamp is primarily situated in the United States and Europe. As illustrated in figure 5a, traded volume exceeds average daily volume around 08:00 UTC, at the start of the regular trading hours in Europe. Volume peaks between 13:00 and 16:00 UTC, at the beginning of the trading day in the United States. After 16:00 UTC, traded volume drops together with the closing of most European exchanges. The U.S. exchanges close around 21:00 UTC and we observe that at the same time the traded volume falls below the average. The lowest average volume is between 03:00 and 06:00 UTC, outside trading hours in both Europe and the United States. Similar results are found by Eross et al. (2017) for the BTC-e exchange. Comparable as in other markets, it is observed that traded volume and price volatility move together (Karpoff 1987). Table 3 provides Pearson's correlation coefficient $\rho$ for correlation between volume and absolute returns.

[10] https://api.bitcoincharts.com/v1/csv/ provides the complete BitCoin trade history of numerous exchanges in several currencies and is used in most academic literature as data source.

[11] As of 07-09-2017, Bitstamp is the third largest exchange based on the last 6-months traded volume in USD/BTC, https://bitcoinity.org/markets/list?currency=USD&span=6m

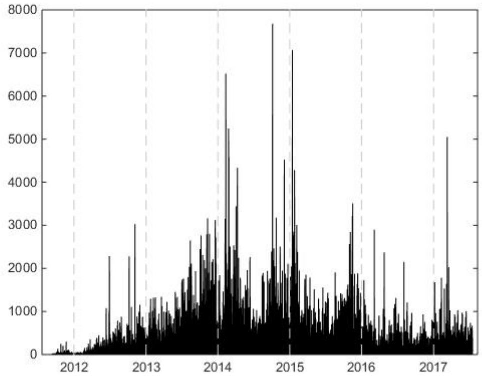
[12] 23-06-2016 has a questionable observation of $p_t = 1.5$, while surrounding prices range around $p_t = 574$. The observation is treated as incorrect and replaced with the average price of the surrounding interval.

**Table 2:** Descriptive statistics of the full sample period

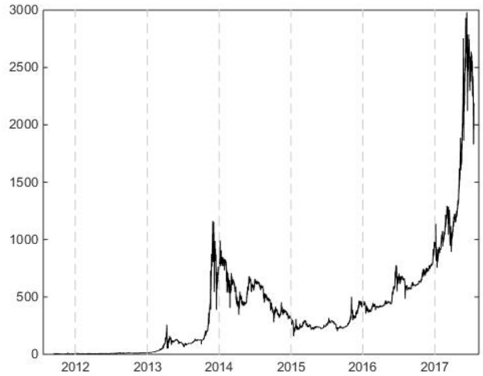
| | |
|---|---|
| Traded volume (BTC) | 19 729 718 |
| Number of trades | 12 374 508 |
| 5-minute observations | 477 773 |
| *Prices (USD)* | |
| Mean | 526.4 |
| Standard deviation | 486.9 |
| Minimum | 12.8 |
| Maximum | 2980.0 |
| *Log returns (USD)* | |
| Mean (bps) | 0.107 |
| Standard deviation (bps) | 44.15 |
| Minimum (bps) | −3689.3 |
| Maximum (bps) | 6108.5 |
| Skewness | 4.52 |
| Kurtosis | 1181.4 |
| Augmented Dickey-Fuller test | -757.5 |
| Ljung-Box Q test | 7676.9 |

*Descriptive statistics of the USD/BTC exchange rate between 01-01-2013 and 17-07-2017.*

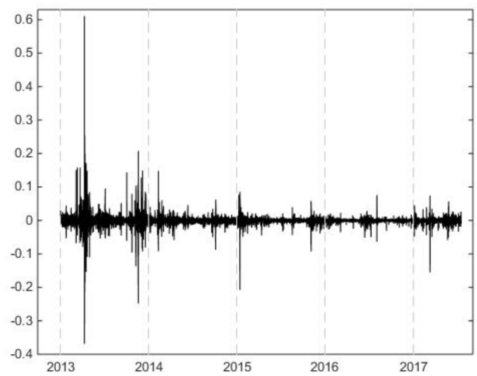
**Figure 4:** BTC/USD traded volume, price and log return




**(a)** Traded volume (₿)



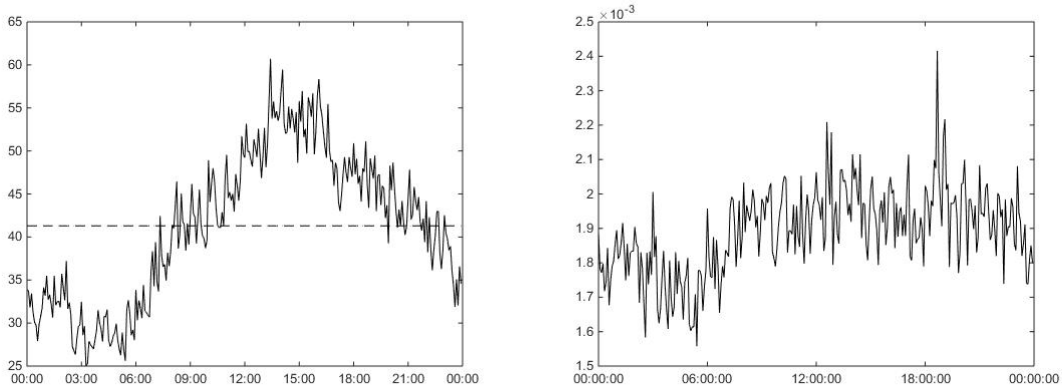

**(b)** Price ($)




**(c)** Returns ($)

*Figure 4a illustrates the traded volume on a 5-min frequency basis, measured in BitCoin, traded on Bitstamp between 13-09-2011 and 17-07-2017. Figure 4b shows the closing prices during the same period. Figure 4c shows the 5-minute log returns over the sample period.*

**Figure 5:** Average intra-day traded volume and volatility (UTC ±00:00)




**(a)** 5-minute traded volume **(b)** 5-minute absolute returns

*Figure 5a shows the average 5-minute traded volume per day between 01-01-2013 and 17-07-2017. The dotted line represents the overall average volume. Figure 5b gives the average 5-minute absolute returns per day between 01-01-2013 and 17-07-2017. The time standard UTC is interchangeable with Greenwich Mean Time.*

**Table 3:** Correlation between traded volume and absolute returns

| Sample | $\rho$ | $p$-value |
|---|---|---|
| Including zero-volume observations | 0.4064 | 0.000 |
| Excluding zero-volume observations | 0.4004 | 0.000 |

*Pearson's correlation coefficient $\rho$ and its significance between 5-min traded volume and absolute returns from 01-01-2013 to 17-07-2017.*

# 4 Performance Metrics

This section provides an overview on how the performance of the technical trading rules is measured. The performance of the trading strategies is evaluated using three criteria: mean excess return, Sharpe ratio and Sortino ratio. The use of the mean excess return and Sharpe ratio metrics is common practice in the literature, see e.g. Sullivan et al. (1999), Qi & Wu (2006) and Hsu et al. (2016). In contrary, the Sortino ratio is rarely used to evaluate technical trading rule performance, but may provide valuable new insights. Performance is measured based on excess performance with respect to a buy-and-hold strategy.

Investment strategies in the foreign exchange market are different compared to the equity market in the sense that short and long positions in currencies are obtained differently compared to stocks. A long position in the foreign currency is obtained by borrowing the local currency in order to buy the foreign currency. During this investment, the investor pays the local interest rate while earning the interest rate of the foreign currency. To switch from a long position to a short position, first the foreign currency is converted to the local currency to repay the borrowed local currency. Secondly, the foreign currency is borrowed and converted to the local currency. Now the investor pays the foreign interest rate and receives the local interest rate. Therefore, generally in the academic literature, the excess return of trading rule $k$ at time $t$, excluding transaction costs, is defined as in Qi & Wu

(2006) by

$$r^e_{k,t} = \left[\ln\left(\frac{p_t}{p_{t-1}}\right) + i^*_t - i_t\right] s_{k,t-1}, \tag{4.1}$$

where $i_t$ and $i^*_t$ are the local and foreign risk-free interest rate from time $t-1$ to $t$, respectively. However, in this paper the interest rate differential is excluded from our analysis. First of all, as mentioned by Qi & Wu (2006), most authors ignore the interest rate differential due to its limited impact on the excess returns of the trading rules. Sweeney (1986) show that excess returns depend primarily on movements in the exchange rate and Qi & Wu (2006) mention that consideration of the interest rate differential in their study results in similar findings. Secondly, the interest rate on U.S. T-bills is historically low during the sample period and negligible compared to exchange rate movements of the BitCoin and transaction costs. Since the effect of the interest rate differential is opposite between short and long positions, the impact flattens out even more. Finally, no commonly accepted BitCoin interest rate yet exists. Moreover, although it is possible to borrow and lend BitCoins, no reliable data on interest rates is available. Therefore, we define returns by

$$r^e_{k,t} = \ln\left(\frac{p_t}{p_{t-1}}\right) s_{k,t-1}. \tag{4.2}$$

Transaction costs are not included in the returns yet. By reporting break-even transaction costs, the reader can determine whether the trading rules are profitable based on the transaction costs applicable to the reader himself. The trading rules are tested for profitability relative to a benchmark buy-and-hold strategy $r_0$. The benchmark strategy of having a continuous long position (buy-and-hold) in the market is defined by:

$$r_{0,t} = \ln\left(\frac{p_t}{p_{t-1}}\right).$$

The performance of the trading strategies is evaluated using three criteria. The mean excess return performance metric of trading rule $k$ is defined as

$$M^e_k = \frac{1}{T}\sum_{t=1}^{T} r^e_{k,t} - \frac{1}{T}\sum_{t=1}^{T} r_{0,t}, \tag{4.3}$$

where $T$ is defined as the number of observations in the sample period. The second performance measure, the Sharpe ratio, measures the average excess return per unit of total risk. The Sharpe ratio performance metric of trading rule $k$ is defined as

$$M^s_k = sh(r^e_{k,t}) - sh(r_{0,t}) \tag{4.4}$$

where the form of $sh(.)$ is given by

$$sh(r^e_{k,t}) = \frac{E\left[r^e_{k,t}\right]}{\sqrt{E\left[(r^e_{k,t})^2\right] - E\left[r^e_{k,t}\right]^2}} \tag{4.5}$$

and where $E[.]$ is the expected value. The Sharpe ratio is often regarded as more informative as it adjusts returns for associated volatility (Hsu et al. 2016). Suppose two trading rules earn the same level of mean excess return, but the Sharpe ratio of the first trading rule is twice as large. Doubling the position in the second trading rule doubles the return while having the same level as risk compared to a position in the first trading rule. Nonetheless, the Sharpe ratio has a few limitations. The Sharpe ratio does not distinguish between upside and downside volatility. Extreme returns affect the Sharpe ratio drastically, often undesirable in case of positive returns.

The Sortino ratio is a modification of the Sharpe ratio which estimates the average excess return relative to downside deviation rather than standard deviation. Sortino & Price (1994) argued that if there exists a minimal acceptable rate of return, only volatility associated with returns below this level should be considered as risk. Even Markowtiz (1991) recognized that the use of downside deviation is a more appropriate risk measure, but that optimization computations were not possible at the time he developed the modern portfolio theory. The Sortino ratio performance metric of trading rule $k$ is defined as

$$M_k^z = sor(r_{k,t}^e) - sor(r_{0,t}), \tag{4.6}$$

where the form of $sor(.)$ is given by

$$sor(r_{k,t}^e) = \frac{E\left[r_{k,t}^e\right] - r_{MAR}}{\sqrt{\frac{1}{T}\sum_{i=1}^{T}\left[\min(r_{k,t}^e - r_{MAR}, 0)\right]^2}}, \tag{4.7}$$

where $r_{MAR}$ is the minimal acceptable rate of return. Note that in the denominator we determine deviations from $r_{MAR}$ instead of the mean return. In the remainder of the paper we set $r_{MAR} = 0$.

# 5 Data-snooping Tests

When evaluating a single hypothesis, the classical methods of hypothesis testing control the probability of rejecting a true null hypothesis. However, when testing multiple hypotheses on the same dataset, the probability of rejecting a true null hypothesis becomes greater than the nominal significance level of the test. For a large number of hypotheses, the probability of falsely rejecting a null hypothesis may even converge to 1. This phenomenon, referred to as data-snooping, is widely recognized in the academic literature, but often not correctly addressed (Park 2016). As we study a large universe of trading rules tested on the same dataset, data-snooping effects are taken into account. This section provides a brief overview of the literature and explains the four methods we adopt to mitigate data-snooping issues: White's Reality Check, the superior predictive ability test, the stepM test and the stepwise superior predictive ability test.

Data-snooping biases are widely recognized in the academic literature as a significant issue. A first notice of data-snooping effects is given by Jensen & Bennington (1970), who wrote:

> Likewise, given enough computer time, we are sure that we can find a mechanical trading rule which 'works' on a table of random numbers - provided of course that we are allowed to test the rule on the same table of numbers which we used to discover the rule. (p. 470)

Lo & MacKinlay (1990) were the first to quantify the effects of data-snooping. Brock et al. (1992) acknowledge the dangers of data-snooping, but are not yet able to conduct a comprehensive test across all trading rules and account for the bias. The first widely accepted method to account for the effects of data-snooping, proposed in a seminal paper by White (2000), is called White's Reality Check. White's Reality Check extends the work of Diebold & Mariano (1995) and West (1996) regarding testing hypotheses about predictive ability. Among others, Sullivan et al. (1999) and Qi & Wu (2006) use White's Reality Check to test the performance of a universe of trading rules in the stock and foreign exchange market, respectively. Both studies conclude that the technical trading rules lose their predictive power when controlling for data-snooping.

White's Reality Check tests the null hypothesis that the model selected in a search over $K$ models has no predictive superiority over a given benchmark model. The test evaluates the distribution of a performance measure considering the complete universe of models that was used to select the best-performing model. The Reality Check tests the null-hypothesis

$$H_0 : \max_{k=1,\dots,K} E[M_k] \leq 0 \tag{5.1}$$

to assess whether there exists a superior rule that does not outperform the benchmark. Rejection will indicate that the best-performing trading rule achieves superior returns compared to the benchmark. In order to ensure that population moments are well-defined, it is assumed that $M_k$ is stationary over time and strong $\alpha$-mixing. Moreover, these assumptions validate the use of Politis & Romano (1994)'s stationary bootstrapping procedure discussed below. Under these conditions the central limit theorem

$$\Big(M_k - E[M_{k,t}]\Big)\sqrt{T} \xrightarrow{d} N(0,\Omega) \tag{5.2}$$

applies, where $E[M_{t,k}]$ is the expected performance measure at time $t$.[13]

Realizations of $N(0,\Omega)$ are drawn by applying the stationary bootstrap developed by Politis & Romano (1994). By randomly drawing adjacent blocks of observations from a time series and assembling them together, stationary pseudo-time series are created. The blocks are sampled with replacement and excess observations in the last block are discarded. The variable block length follows a geometric distribution. In line with Sullivan et al. (1999), we set the parameters of this distribution such that the average block length $q$ equals 10.[14] In line with the literature, this process is repeated $B = 500$ times. For each bootstrap sample $b = 1, ..., B$, the performance metrics are determined using the re-sampled returns of the trading rules and benchmark as in equations (4.3), (4.4) and (4.6). The corresponding bootstrapped performance metrics are defined by $\bar{M}^e_{k,b}$, $\bar{M}^s_{k,b}$ and $\bar{M}^z_{k,b}$, respectively. The following statistic is constructed

$$\bar{V}_{K,b} = \max_{k=1,\dots,K} (\bar{M}_{k,b} - M_k)\sqrt{T}, \quad b = 1,\dots,B, \tag{5.3}$$

which is the maximum of $N(0,\Omega)$ approximated by the stationary bootstrap. White constructs the following statistic to make proper statistical inferences

$$\bar{V}_K = \max_{k=1,\dots,K} M_k\sqrt{T}. \tag{5.4}$$

[13]For the mean excess performance metric, $M^e_{t,k}$ is defined as $r^e_{k,t} - r_{0,t}$. For the Sharpe ratio, $M^s_{t,k}$ is defined as $M^e_{t,k}/\hat{\sigma}_k$, where $\hat{\sigma}_k$ is the estimated standard deviation of the excess return of trading rule $k$. A similar procedure is used for the Sortino ratio. For further details we refer to Hsu et al. (2010), page 472 - 473 and 478.

[14]The optimal block length depends on the dependence of the data. Using the estimator for optimal block length proposed in Politis & White (2004), it is observed that the optimal block length fluctuates heavily for the return vectors of the different trading rules. A consensus on the optimal block length for the full dataset is hard to determine. Fortunately, Sullivan et al. (1999) and Hsu & Kuan (2005) show that their $p$-values are not sensitive to the choice of average block length $q \in \{100, 10, 2\}$. We set smoothing parameter $q = 10$, which is similar as in the available related literate, including Sullivan et al. (1999), White (2000), Qi & Wu (2006), Hsu et al. (2016) and Shynkevich (2016). We are aware that the literature does not consider high-frequency data, but more comparable references are not available.

This statistic is based on equation (5.2), but obtained under the least favorable configuration, i.e. zero mean. White's $p$-value is then determined by comparing $\bar{V}_{K,b}$ and $\bar{V}_K$. As the maximum of a normal distribution is not normally distributed, the percentile method is appropriate. White's $p$-value is thus defined by

$$p^{White} = \frac{1}{B}\sum_{b=1}^{B} \mathbb{1}_{\bar{V}_{K,b} > \bar{V}_K}. \tag{5.5}$$

By taking the maximum value over all $K$ trading rules in (5.4) and (5.3), White's $p$-value incorporates the bias of data-snooping from the search over $K$ trading rules. For the technical details and the derivation of equations (5.3), (5.4) and (5.5), in combination with the stationary bootstrap, we refer to Appendix B in Sullivan et al. (1999), which replicates the main results of White (2000).

The superior predictive ability test (SPA) is a modified version of White's Reality Check developed by Hansen (2005). Hansen observed that the null hypothesis of White's Reality Check is based on the least favorable configuration, which causes the test to lose its power drastically when many poor and uninformative rules are included. Hansen shows that the power can be improved substantially by using a re-centered and studentized test statistic. He proposes to use the studentized test statistic $\bar{V}_{SPA}$ defined as

$$\bar{V}_{SPA} = \max\left(\max_{k=1,\ldots,K} \frac{M_k\sqrt{T}}{\sqrt{\hat{w}_k^2}}, 0\right) \tag{5.6}$$

to substitute (5.4), where $\hat{w}_k^2$ is a consistent estimator of $w_k^2 = var(M_k\sqrt{T})$, calculated using the bootstrap. The following statistic is defined to replace (5.3),

$$\bar{V}_{SPA,b} = \max\left(\max_{k=1,\ldots,K} \frac{(\bar{M}_{k,b} - M_k)\sqrt{T}\mathbb{1}_{M_k \geq -A}}{\sqrt{\hat{w}_k^2}}, 0\right), \quad b = 1, \ldots, B \tag{5.7}$$

where $A = \sqrt{2\left(\frac{\bar{w}_k^2}{T}\right)\log\log T}$. The $p$-value of the SPA-test is then defined as

$$p^{SPA} = \frac{1}{B}\sum_{b=1}^{B} \mathbb{1}_{\bar{V}_{SPA,b} > \bar{V}_{SPA}}. \tag{5.8}$$

Hsu & Kuan (2005) and Lunde & Hansen (2005) both confirm that the SPA test is more powerful than White's Reality Check. For the technical details and derivation of the SPA-test we refer to sections 2 and 3 of Hansen (2005).

A drawback of both White's Reality Check and the superior predictive ability test is that they only identify the significance of the best performing model, while an investor might be interested in the significance of multiple trading rules. In order to circumvent this drawback, Romano & Wolf (2005) introduced a stepwise version of White's Reality Check, the stepM test, which is able to identify all significant trading rules. The studentized stepM test, building on the definitions and bootstrap described above, consists of the following steps (Romano & Wolf 2005):

1. Construct the studentized empirical null distribution by first defining

$$z_b = \sqrt{T}\max_{k=1,\ldots,K}\left[\frac{\bar{M}_{k,b} - M_k}{\sigma_k}\right], \quad b = 1, \ldots, B, \tag{5.9}$$

   where $\sigma_k$ the standard deviation of the bootstrapped performance metrics of trading rule $k$.

2. Then rank $\{z_b\}_{b=1,\dots,B}$ in descending order and collect its $(1-\alpha)$-th quantile, denoted by $q(\alpha)$. For each trading rule $k$, reject the null-hypothesis at the $n$-th step if $\dfrac{\sqrt{T}M_k}{\sigma_k} > q(\alpha)$.

3. Restart at step 1, letting $M_k = 0$ and $\bar{M}_{k,b} = 0$ for all trading rules $k$ for which the null hypothesis is rejected in step 2. If no null hypothesis is rejected for the remaining $k$ trading rules, stop and collect the significant trading rules.

The stepM test identifies all significant trading rules at a $(1-\alpha)\%$-level. Although this is a big advantage over the SPA test, it shares the same shortcomings in predictive power as White's Reality Check mentioned above. The natural extension, proposed by Hsu et al. (2010), is the stepwise-SPA test, which combines the (studentized) stepM test with the SPA test. The stepwise-SPA test follows the same steps as the stepM test given above, expect that the definition of the empirical null distribution in (5.9) is replaced by

$$z_b = \sqrt{T} \max_{k=1,\dots,K} \left[ \frac{\bar{M}_{k,b} - M_k + M_k \mathbb{1}_{M_k \leq -A}}{\sqrt{\hat{w}_k^2}} \right], \quad b = 1, \dots, B. \tag{5.10}$$

Hsu et al. (2016) provides an overview on the implementation of the stepwise-SPA test.

We use all four data-snooping tests to identify the significance of the technical trading rules. The SSPA en stepM test are used to identify which trading rules are significant at a 5% confidence level. We use *both* the SSPA and stepM test in order to validate the results, gain insights regarding the relative power of both tests and observe whether the universe of trading rules consists of many uninformative strategies. White's Reality Check and the SPA test are used to determine $p$-values of the *best performing* technical trading rule. Note that White's Reality Check and the SPA test are both related to their stepwise parent. If the stepM test indicates zero significant strategies, $p^{White}$ of the best performing trading rule exceeds 5%. Similarly, if the SSPA test indicates zero significant strategies, $p^{SPA}$ of the best performing trading rule exceeds 5%.

White's Reality Check, the SPA, stepM and SSPA test are the most popular, but not the only tests available to handle the data-snooping bias. The main critic on the data-snooping tests described above is their conservativeness, caused by strongly controlling the false rejection of trading rules (Zarrabi et al. 2017). The *false discovery rate* methodology (Benjamini & Hochberg (1995), Barras et al. (2010)) allows a number of false discoveries to improve the power of the test. Bajgrowicz & Scaillet (2012) use the false discovery rate to test the same universe of trading rules as Sullivan et al. (1999) and report little evidence of significant profitability of the technical trading rules. As we aim to detect rules which are exclusively not profitable due to luck, it is decided to exclude the false discovery rate from the analysis. A *model confidence set*, proposed by Hansen et al. (2011), is a subset of models that contains the best model with a certain confidence level. A major advantage of this method is that it is not necessary to specify a benchmark model. However, as we have a natural benchmark in our study, the model confidence set methodology is excluded.

## 6 Empirical Results

Both the SSPA and the stepM test report numerous trading rules which significantly outperform the buy-and-hold benchmark strategy at a 5% significance level. Moreover, the best performing trading rule is highly significant and the presence of transaction costs does not necessarily eliminate its profitability. Nonetheless, market efficiency seems to increase over time. Section 6.1 and 6.2 report the significance and profitability of the trading rules. Section 6.3 explains how trading rule performance behaves when transaction costs are included. Section 6.4 describes the persistence of the results by reporting sub-sample analyses.

### 6.1 Significance of the Technical Trading Rules

The SSPA and stepM test report numerous significant trading rules. Table 4 shows the number of significant strategies per performance metric and class of trading rules as identified by the SSPA and stepM test at a 5% significance level.[15] Considering the Sharpe ratio performance metric, the SSPA test indicates 541 significant strategies, 16.3% of the tested universe of trading rules.[16] The number of significant strategies is fairly consistent over the different performance metrics.[17] The most striking observation is that trend-reversal strategies seem to perform substantially better than trend-following trading rules. Apparently, the BitCoin exchange rate shows trend-reversal (volatile) behavior at a 5-minute frequency.[18] In the remainder of this paper, we refer to the set of significant strategies as the collection of strategies indicated as significant by the SSPA test using the Sharpe ratio performance metric, unless stated otherwise.

When testing many strategies on high-frequency data without penalizing the number of transactions, it is likely that strategies conducting many transactions yield the highest return. Figure 6 confirms this hypothesis and indirectly explains the insignificance of the on-balance volume average rules. Figure 6 shows the trading frequency of all the strategies in the tested universe. The dark dots represent the significant strategies and the gray dots represent the insignificant trading rules. Except for the filter rules, the significant strategies are primarily trading rules which trade frequently. The average number of trades of the significant strategies over the full sample period is 34 336, once every 70 minutes on average. Table 5 shows the number of significant trading strategies segmented over their delay and holding period parametrization. The segregation per delay period shows that increasing the length of the delay filter drastically reduces the number of significant strategies. A delay period reduces the number of transactions and therefore the potential of high returns. Incorporating a long delay period reduces the number of transactions with such a magnitude that the trading rule becomes useless. In fact, when the length of the delay period equals $d = 3$, none of the trading rules generate any trading signal.[19] This observation confirms the volatile and trend-reversal behavior of the BitCoin price. Apparently, signals do not remain valid for more than three intervals due to the high

[15] Consistent with Hsu et al. (2010), the number of strategies identified as significant by the SSPA test is greater or equal compared to the stepM test.

[16] The number of significant trading rules is relatively insensitive to the significance level. At a 10% and 1% significance level, the number of significant strategies are 562 and 496, respectively.

[17] The literature does not convey a clear picture on support of this finding: Hsu et al. (2010) report a similar number of significant strategies for the mean excess return and sharpe ratio performance metrics, while Hsu et al. (2016) report a different number of significant trading rules per performance metric.

[18] Consistent with Hudson et al. (2017) who show that trend-reversal strategies perform better when the sampling frequency increases.

[19] The average number of trades of the full universe of trading rules with delay period of length $d = 0$ is 49 457, of $d = 1$ is 7034 and of $d = 3$ is 0.

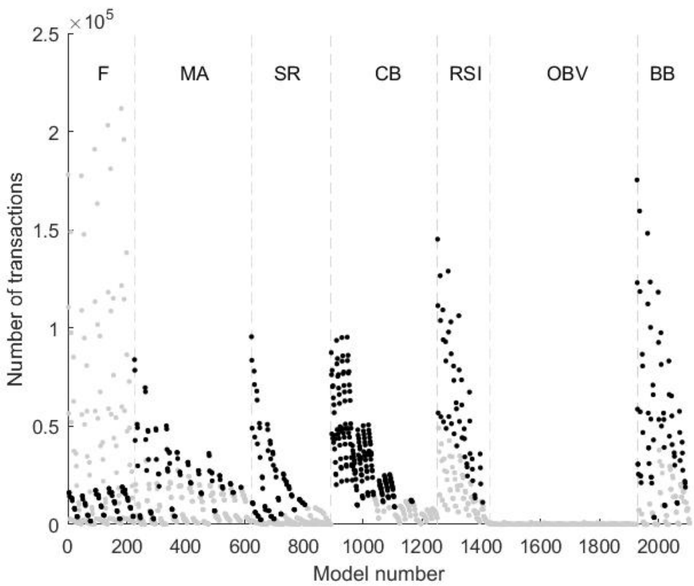
**Table 4:** Number of significant technical trading rules per type

| Class of trading rule | Tested | Mean excess return | | Sharpe ratio | | Sortino ratio | |
|---|---|---|---|---|---|---|---|
| | | SSPA | stepM | SSPA | stepM | SSPA | stepM |
| *Standard strategies* | | | | | | | |
| Filter | 225 | 66 | 66 | 66 | 59 | 66 | 62 |
| Double moving average | 396 | 0 | 0 | 0 | 0 | 0 | 0 |
| Support & resistance | 270 | 18 | 18 | 21 | 8 | 17 | 12 |
| Channel breakout | 360 | 0 | 0 | 0 | 0 | 0 | 0 |
| Relative strength indicator | 180 | 47 | 47 | 48 | 42 | 48 | 43 |
| On-balance volume average | 495 | 0 | 0 | 0 | 0 | 0 | 0 |
| Bollinger bands | 180 | 48 | 48 | 48 | 45 | 48 | 48 |
| *Contrarian strategies* | | | | | | | |
| Double moving average | 396 | 78 | 78 | 84 | 57 | 86 | 66 |
| Support & resistance | 270 | 58 | 58 | 59 | 48 | 60 | 54 |
| Channel breakout | 360 | 194 | 194 | 197 | 182 | 194 | 186 |
| Bollinger bands | 180 | 18 | 18 | 18 | 14 | 18 | 14 |
| Total | 3312 | 527 | 527 | 541 | 455 | 537 | 485 |

*The number of significant technical trading rules per class of rules, performance metric and testing method at a 5% significance level. The trading rules are evaluated over the full sample period. The $2^{nd}$ column gives the total number of strategies tested per class of trading rules.*

price volatility. Interestingly however, the length of the holding period seems to have less influence on the significance of the strategies. Despite the reduction of the number of transactions caused by a holding period, the strategies will generate trading signals, but at a lower frequency.

**Figure 6:** Distribution of the significant trading rules with respect to trading frequency




*The figure shows the trading frequency of all trading rules in the tested universe. The dark dots represents the number of trades of all significant trading rules, including the contrarian rules, as indicated by the SSPA test. The gray dots represent the insignificant strategies. The x-axis represents the model number, the dashed lines separate the different trading rule classes.*

**Table 5:** Parametrization characteristic of the significant trading rules

| **Performance metric** | **Delay period $d$** | | | **Holding period $c$** | | |
|---|---|---|---|---|---|---|
| | $d = 0$ | $d = 1$ | $d = 3$ | $c = 0$ | $c = 2$ | $c = 6$ |
| Mean excess return | 230 | 103 | 0 | 178 | 176 | 173 |
| Sharpe ratio | 235 | 109 | 0 | 182 | 181 | 178 |
| Sortino ratio | 238 | 105 | 0 | 180 | 179 | 178 |

*The number of significant technical trading rules segmented over the trading rule parameterization of the delay and holding period. Values are obtained using the SSPA test. As the delay filter is excluded in the channel breakout rules, the sum of the significant rules over the delay filter does not equal the total significant rules.*

### 6.2 Best Performing Technical Trading Rule

The best performing trading rule is defined as the strategy with the highest performance metric. Table 6 shows statistics of the best performing technical trading rule over the full sample period. The best performing trading rule is the bollinger band $BB(4, 0.25, 0, 0)$ strategy. This result is consistent for all performance metrics.[20] This strategy yields a mean excess log return of 3.816 basis points per 5-minute interval. The results are highly significant as indicated by the $p$-values obtained from White's Reality Check and the SPA test.[21] As illustrated in figure 7a, the trading rule manages to exploit both the upward and downward price deviations. Figure 7b plots the cumulative returns over the first 3000 time intervals together with squared returns to indicate periods of high volatility. It is concluded from the figure that the trading rule is primarily profitable during periods of high volatility, particularly when volatility peaks. Figure 11a compares the cumulative log returns of all bollinger band rules and illustrates that multiple variations are highly profitable. The bollinger band rules are the only strategies which include information on price volatility when generating trading signals. Apparently, price volatility is an informative predictor for the BitCoin price. Figure 12 in the appendix provides an example to show how the trading signals of the $BB(4, 0.25, 0, 0)$ rule are generated.

**Table 6:** Best performing technical trading rule over the full sample period

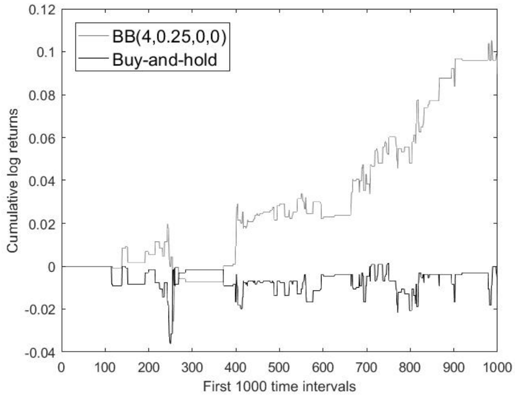
| **Performance metric** | **Trading rule with highest return** | | | | | | |
|---|---|---|---|---|---|---|---|
| | Rule | $M_k$ (bps) | Bench (bps) | $p^{White}$ | $p^{SPA}$ | Trades | BETC (bps) |
| Mean excess return | $BB(4, 0.25, 0, 0)$ | 3.816 | 0.107 | 0.000 | 0.000 | 148 173 | 6.32 |
| Sharpe ratio | $BB(4, 0.25, 0, 0)$ | 0.087 | 0.002 | 0.000 | 0.000 | 148 173 | 6.32 |
| Sortino ratio | $BB(4, 0.25, 0, 0)$ | 0.134 | 0.003 | 0.000 | 0.000 | 148 173 | 6.32 |

*Significance and profitability of the best performing technical trading rule at a 5% significance level. The number of trades is defined as the number of switches between a long and a short position. (One-way) break-even transaction costs (BETC) are determined by dividing the sum of log returns by twice the total number of trades.*

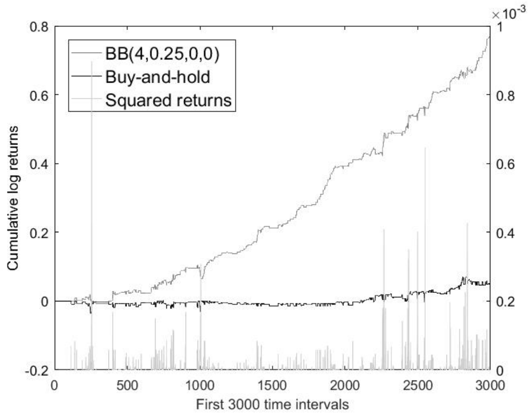
[20] Although Qi & Wu (2006) select equal rules for each performance metric, this finding is generally not consistent with the literature, see e.g. Sullivan et al. (1999), Hsu et al. (2010) and Hsu et al. (2016).

[21] The $p$-values seem low, but similar results are reported by, among others, Sullivan et al. (1999), Qi & Wu (2006) and Coakley et al. (2016).

**Figure 7:** Return evolution of the $BB(4, 0.25, 0, 0)$ strategy vs. a buy-and-hold strategy




**(a)** Focused cumulative log returns




**(b)** Cumulative log returns vs. volatility

*Figure 7a plots the cumulative log returns of the bollinger band $BB(4, 0.25, 0, 0)$ strategy and a buy-and-hold benchmark over the first 1000 time intervals. In figure 7b the horizon is increased and squared returns are plotted on the right Y-axis to indicate periods of high price volatility.*

Table 7 reports return statistics of the $BB(4, 0.25, 0, 0)$ trading rule. The high kurtosis, magnitude of the minimum and maximum return and standard deviation all reveal that the strategy's return is highly unstable over time, consistent with the stylized facts reported by Menkhoff & Taylor (2007). The maximum drawdown is huge, losing over 15 000 basis points of return within 5 days. As reported in table 6, the total number of trades is 148 173, corresponding to one trade every 16 minutes on average. The ratio of good versus bad trades is remarkably high, with 56 788 profitable trades compared to 17 215 losing trades. Nonetheless, the average loss of a losing trade is higher than the average return of a profitable trade. Note that, as we consider log returns excess of a buy-and-hold benchmark without transaction costs, all long positions yield zero excess return. The average duration of a losing position is over twice as large as the average duration of a profitable position. Hence, the profits from exploiting relatively many small price fluctuations exceed the losses incurred from a few highly losing positions.

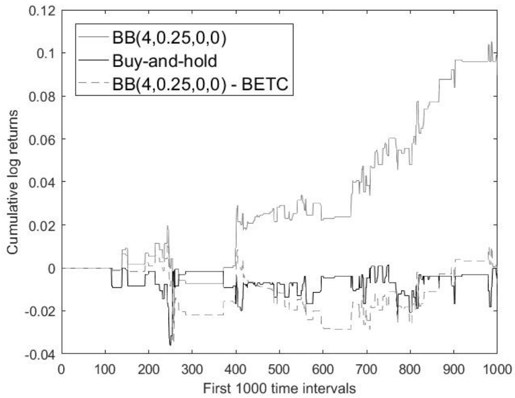
**Table 7:** Return statistics of the $BB(4, 0.25, 0, 0)$ strategy over the full sample period

| | |
|---|---|
| Mean excess log returns $M_k^e$ (bps) | 3.816 |
| Standard deviation (bps) | 56.7 |
| Minimum (bps) | −5051.5 |
| Maximum (bps) | 4236.9 |
| Skewness | 2.02 |
| Kurtosis | 729.4 |
| Maximum drawdown (bps) | 15 111.5 |
| Number of profitable trades | 56 788 |
| Number of losing trades | 17 215 |
| Number of zero-return trades | 74 170 |
| Mean return of profitable trades (bps) | 56.288 |
| Mean return of losing trades (bps) | -79.778 |

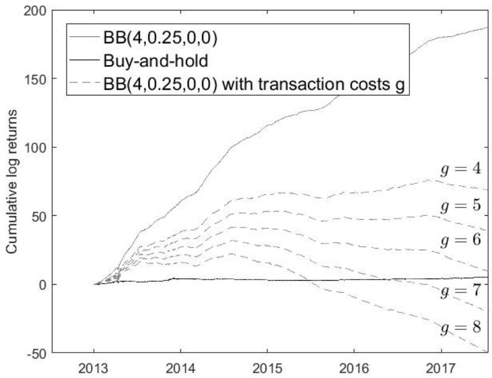
*Descriptive statistic of the returns (excess of the buy-and-hold benchmark) of the $BB(4, 0.25, 0, 0)$ strategy over the full sample period. Return of a trade is defined as the sum of log returns obtained during a period in which the same position is held.*

The impact of transaction costs is substantial at these high trading frequencies and does eliminate the profitability of the best performing trading rule. Table 18 in the appendix provides the fee schedule of the BitStamp exchange. The minimum one-way transaction costs, denoted by $g$, are 10 basis points. The break-even transaction costs of the $BB(4, 0.25, 0, 0)$ strategy are equal to $g = 6.32$ basis points.[22] This level of transaction costs is lower than the transaction costs actually faced by an average or institutional investor. Hence, inclusion of transaction costs does eliminate the profitability of the $BB(4, 0.25, 0, 0)$ strategy. Figures 8a and 8b show the high impact of transaction costs on the trading rule profitability. As shown in figure 8b, a 1 bps difference in transaction costs results in a huge log return difference. Since trading rules selected before penalizing the number of transactions tend to generate frequent trading signals, it is natural that the performance is impacted substantially after including transaction costs.

**Figure 8:** Return sensitivity of the best performing trading rule to transaction costs




**(a)** Focused return evolution




**(b)** Return sensitivity to transaction costs

*Figure 8a shows the cumulative log returns of the $BB(4, 0.25, 0, 0)$ strategy and a buy-and-hold benchmark over the first 1000 time intervals. The dashed line represents the evolution of cumulative log returns when one-way transaction costs equal break-even transaction costs, i.e. $g = 6.32$ basis points. Figure 8a shows the returns over the full sample period. The dashed lines represent the cumulative log returns when transaction costs of $g = 4, 5, 6, 7$ or $8$ basis points are included.*

### 6.3 Transaction Costs

In section 6.2 we evaluated transaction costs by reporting the break-even transaction costs of the best-performing trading rule. In this way the reader can decide whether the transaction costs he actually faces are below the reported break-even transaction costs. Although this proves to be a useful tool, it may not always be appropriate. Trading rules selected before incorporating transaction costs are primarily strategies which generate and execute many trading signals, particularly when trading horizons are short. Incorporating transaction costs from the start leads to other optimal rules with a different trade-off between gross profitability and transaction costs. Another limitation of reporting break-even transaction costs in combination with the best performing trading rule only, is that the break-even transaction costs of the second best strategy might be substantially higher, while the gross

[22]Break-even transaction are defined as the level of one-way transaction costs that will reduce excess returns to exactly zero. Break-even transaction costs are determined by dividing the sum of log returns by twice the total number of trades.

return is only slightly lower. To circumvent these concerns, in this section transaction costs are included from the start.

One-way transaction costs of $g = 13$ basis points are included in all analyses reported in the remainder of section 6. This level of transaction costs corresponds to investors with a monthly traded volume of around USD 2 million, see table 18. Since we consider a level of transaction costs which is actually faced by investors, finding significantly profitable trading rules would serve as evidence of inefficiency of the BitCoin market.[23] Transaction costs are included in line with Qi & Wu (2006), that is, equation (4.2) is substituted with

$$r^e_{k,t} = \ln\left(\frac{p_t}{p_{t-1}}\right) s_{k,t-1} - g|s_{k,t-1} - s_{k,t-2}|, \tag{6.1}$$

where $g$ is the one-way transaction costs. Note that the absolute value of the difference of two trading signals equals two when switching between a long and short position. Section 4 explains the transactions involved when switching between a long and short position in the foreign exchange market and clarifies that one-way transaction costs are incurred twice for every trade.

The number of significant strategies has decreased substantially due to the presence of transaction costs. Table 8 shows the number of significant strategies per performance metric and class of trading rules as identified by the SSPA and stepM test at a 5% significance level. The number of significant strategies dropped from 541 to 22, 0.7% of the tested universe of trading rules.[24] In contrary to the results in table 4, the number of significant strategies is not consistent over the different testing methods. The results confirm that the SSPA test is more powerful than the stepM test, which loses power due to the presence of numerous poorly performing rules.[25] The stepM test only indicates significant rules when testing the mean excess return performance metric. The average number of trades of the significant strategies has decreased from 33 436 to 10 720. In comparison with figure 6, figure 9 shows the reduction of number of trades of the significant strategies per class of trading rules. The low number of trades of the significant *filter* rules before transaction costs result in a small reduction of the number of significant filter rules when transaction costs are included. Interestingly, the on-balance volume average rules remain insignificant, despite their low trading frequency. Table 9 shows the number of significant strategies dividend over the parametrization of the delay and holding period length. In comparison with table 5, particularly strategies without a delay period have become insignificant due to the presence of transaction costs. Apparently, the trade-off between capturing all trends with frequent trading and exploiting stronger movements with reduced transaction costs, has shifted in favor of the latter.

The best performing trading rule has changed due to the presence of transaction costs. Table 10 shows that the trading rules with highest performance are now the filter $F(3, 0.001, 1, 0)$ and $F(3, 0.001, 1, 2)$ strategies, generating the same trading positions. This result is consistent for all performance metrics. The total number of trades of the $F(3, 0.001, 1, 0)$ strategy is 10 707, trading once every 223 minutes on average, 14 times less compared to the $BB(4, 0.25, 0, 0)$ trading rule. As illustrated in figure 11, the $BB(4, 0.25, 0, 0)$ trading rule has become unprofitable due to the inclusion of transaction costs. The $F(3, 0.001, 1, 0)$ strategy yields a mean excess log return of 0.379 basis points

[23] One-way transaction costs of $g = 13$ basis points is comparable with other major exchanges, such as Bitfinex and bitFlyer

[24] The number of significant trading rules with transaction costs is relatively sensitive to the significance level. At a 10% and 1% significance level, the number of significant strategies are 43 and 6, respectively.

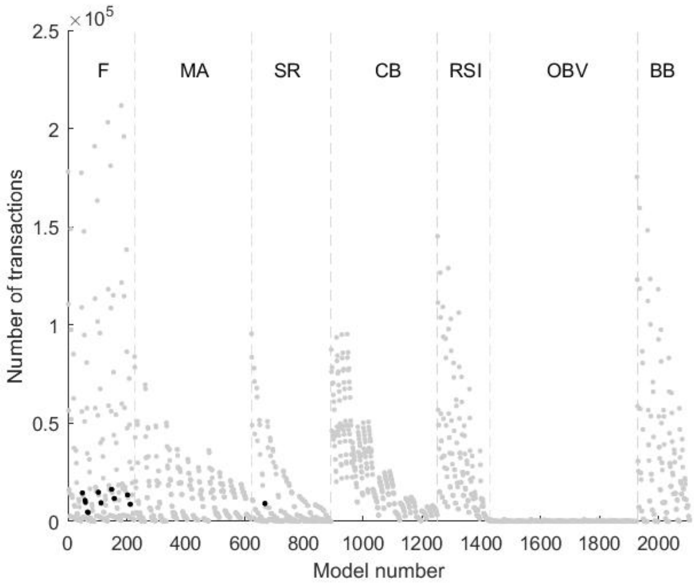
[25] Excluding the contrarian trading rules reduces the difference between the number of significant strategies found by the SSPA and stepM test.

**Table 8:** Number of significant technical trading rules per type with transaction costs

| Class of trading rule | Tested | Mean excess return | | Sharpe ratio | | Sortino ratio | |
|---|---|---|---|---|---|---|---|
| | | SSPA | stepM | SSPA | stepM | SSPA | stepM |
| *Standard strategies* | | | | | | | |
| Filter | 225 | 16 | 16 | 20 | 0 | 20 | 0 |
| Double moving average | 396 | 0 | 0 | 0 | 0 | 0 | 0 |
| Support & resistance | 270 | 0 | 0 | 0 | 0 | 0 | 0 |
| Channel breakout | 360 | 0 | 0 | 0 | 0 | 0 | 0 |
| Relative strength indicator | 180 | 0 | 0 | 0 | 0 | 0 | 0 |
| On-balance volume average | 495 | 0 | 0 | 0 | 0 | 0 | 0 |
| Bollinger bands | 180 | 0 | 0 | 0 | 0 | 0 | 0 |
| *Contrarian strategies* | | | | | | | |
| Double moving average | 396 | 0 | 0 | 0 | 0 | 0 | 0 |
| Support & resistance | 270 | 1 | 1 | 2 | 0 | 2 | 0 |
| Channel breakout | 360 | 0 | 0 | 0 | 0 | 0 | 0 |
| Bollinger bands | 180 | 0 | 0 | 0 | 0 | 0 | 0 |
| Total | 3312 | 17 | 17 | 22 | 0 | 22 | 0 |

*The number of significant technical trading rules per class of rules, performance metric and testing method at a 5% significance level. The trading rules are evaluated over the full sample period and one-way transaction costs are set to $g = 13$ basis points. The $2^{nd}$ column gives the total number of strategies tested per class of trading rules.*

**Figure 9:** Distribution of the significant trading rules with respect to trading frequency with transaction cost




*The figure shows the trading frequency of all trading rules in the tested universe. One-way transaction costs are set to $g = 13$ basis points. The dark dots represents the number of trades of all significant trading rules, including the contrarian rules, as indicated by the SSPA test. The gray dots represent the insignificant strategies. The x-axis represents the model number, the dashed lines seperate the different trading rule classes.*

**Table 9:** Parametrization characteristic of the significant trading rules with transaction costs

| **Performance metric** | **Delay period $d$** | | | **Holding period $c$** | | |
|---|---|---|---|---|---|---|
| | $d = 0$ | $d = 1$ | $d = 3$ | $c = 0$ | $c = 2$ | $c = 6$ |
| Mean excess return | 1 | 16 | 0 | 8 | 7 | 2 |
| Sharpe ratio | 2 | 20 | 0 | 10 | 10 | 2 |
| Sortino ratio | 2 | 20 | 0 | 10 | 10 | 2 |

*The number of significant technical trading rules segmented over the trading rule parameterization of the delay and holding period. Values are obtained using the SSPA test. One-way transaction costs are set to $g = 13$ basis points. As the delay filter is excluded in the channel breakout rules, the sum of the significant rules over the delay filter does not equal the total significant rules.*

per 5-minute interval. Clearly, the optimal log return has decreased substantially after including transaction cost, however the trading rule is still profitable. Figure 13 shows the cumulative excess log returns over the full sample period. The graph illustrates that the returns of the strategy are mainly generated during 2013, 2014 and 2017.

The results are highly significant according to the SPA test, however White's Reality Check indicates the trading rule as insignificant when evaluated using the Sharpe and Sortino ratio. This observation supports the claim that the SPA test is more powerful than White's Reality Check. The $p$-values in table 10 confirm the connection between the four data-snooping tests: the results of White's Reality Check correspond with the findings of the stepM test, while the results of the SPA test coincide with the SSPA test. When using the mean excess return performance metric, the stepM test indicates 17 significant strategies and White's Reality Check reports a $p$-value less than 5% for the optimal trading rule. For the Sharpe and Sortino ratio, the stepM test indicates zero significant strategies and White's Reality Check reports $p$-values above 5%. Similarly, for all performance metrics, the SSPA test indicates significant trading rules and the SPA test reports $p$-values above 5%.

Table 11 reports return statistics of the $F(3, 0.001, 1, 0)$ trading rule. Similar as the $BB(4, 0.25, 0, 0)$ strategy, the high standard deviation, kurtosis and maximum drawdown indicate that excess returns are highly unstable over time. In contrary to the results reported in table 7, the number of profitable trades is lower compared to the number of losing trades. Note however that, due to the presence of transaction costs all long positions are losing compared to the buy-and-hold benchmark strategy. The mean return of a profitable trade is substantially higher than the mean loss of a losing trade.

**Table 10:** Best performing technical trading rule over the full sample period with transaction costs

| **Performance metric** | **Trading rule with highest return** | | | | | |
|---|---|---|---|---|---|---|
| | Rule | $M_k$ (bps) | Bench (bps) | $p^{White}$ | $p^{SPA}$ | Trades |
| Mean excess return | $F(3, 0.001, 1, 0)^{\star}$ | 0.379 | 0.107 | 0.002 | 0.002 | 10 707 |
| Sharpe ratio | $F(3, 0.001, 1, 0)^{\star}$ | 0.008 | 0.002 | 0.208 | 0.004 | 10 707 |
| Sortino ratio | $F(3, 0.001, 1, 0)^{\star}$ | 0.012 | 0.003 | 0.138 | 0.004 | 10 707 |

$^{\star}F(3, 0.001, 1, 2)$ *has equal trading signals, performance and significance.*
*Significance and profitability of the best performing technical trading rule at a 5% significance level. The number of trades is defined as the number of switches between a long and a short position. One-way transaction costs are set to $g = 13$ basis points.*

**Table 11:** Return statistics of the $F(3, 0.001, 1, 0)$ strategy over the full sample period with transaction costs

| | |
|---|---|
| Mean excess log returns $M_k^e$ (bps) | 0.379 |
| Standard deviation (bps) | 67.5 |
| Minimum (bps) | −12 243.0 |
| Maximum (bps) | 7378.8 |
| Skewness | -11.41 |
| Kurtosis | 3256.0 |
| Maximum drawdown (bps) | 16 823.7 |
| Number of profitable trades | 2466 |
| Number of losing trades | 8239 |
| Number of zero-return trades | 2 |
| Mean return of profitable trades (bps) | 295.600 |
| Mean return of losing trades (bps) | -66.538 |

*Descriptive statistic of the returns (excess of the buy-and-hold benchmark) of the $F(3, 0.001, 1, 0)$ strategy over the full sample period. The return of a trade is defined as the sum of log returns obtained during a period in which the same position is maintained. One-way transaction costs are set to $g = 13$ basis points.*

### 6.4 Subperiod Analysis

The performance of the trading rules is not persistent over the full sample period. Dividing the full sample period in subperiods allows us to test for persistence in the results. Moreover, as mentioned by Thaler (1987), using subsamples is another way to avoid data-mining effects. This section provides a subperiod analysis and shows that the BitCoin market has become more efficient over time.

We split the data in 5 subsamples, comprising of all available data of 2013, 2014, 2015, 2016 and 2017, respectively. Given that the full sample period ends in July 2017, the number of observations in the last subperiod is around half of the other subsamples. Descriptive statistics of the subsamples are given in table 19. The dashed lines in figures 4a, 4b and 4c distinguish the subsamples and show the behavior of the BitCoin price over the different periods. Mean returns fluctuate substantially over the subsamples, but are only negative during subperiod 2. The average number of trades is particularly high during the last subperiod, while subsample 4 is characterized by low traded volume and low number of trades. For further characteristics of the subperiods we refer to table 19 in the appendix.

The results obtained in section 6.3 are not persistent over the 5 subsamples. Table 12 reports the results of the subperiod analysis with one-way transaction costs of $g = 13$ basis points. The number of significant strategies as indicated by the SSPA and stepM test at a 5% significance level tends to deteriorate over time. In fact, after 2014 all strategies are marked as insignificant. This may serve as evidence that the Bitcoin market has become more efficient over time.

These results are consistent over the different performance metrics and data-snooping tests. The trading rule with the highest return is not consistent over the subperiods and optimal returns tend to deteriorate over time. Only for subsamples 2013 and 2014, the best performing trading rule is significant at a 5% confidence level. Subsample 2013 is the only period for which the optimal trading rule is not consistent over the different performance metrics. Interestingly, the $F(3, 0.001, 1, 0)$ strategy is in none of the subperiods indicated as the best performing trading rule. Returns of the best performing strategies in 2013 and 2014 are large compared to the average return over the full sample period achieved by the $F(3, 0.001, 1, 0)$ trading rule. However, after 2014, returns decrease and the optimal strategies become insignificant. By consulting table 19, we conclude that the performance of the selected trading rules is consistent with the stylized fact that trading rules tend to have higher returns during more volatile periods.

**Table 12:** The significance and profitability of the technical trading rules over the subsamples with transaction costs

**(a)** Mean excess returns

| **Sample** | **$H_0$ rejected** | | **Rule with highest return** | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SSPA | stepM | Rule | $M_k^e$ (bps) | Bench (bps) | $p^{White}$ | $p^{SPA}$ | Trades |
| Subsample 1 | 31 | 31 | $F(24, 0.0005, 1, 0)^\star$ | 1.175 | 0.382 | 0.014 | 0.010 | 3370 |
| Subsample 2 | 44 | 44 | $SR^c(3, 0.005, 0, 2)$ | 0.504 | -0.078 | 0.014 | 0.000 | 2062 |
| Subsample 3 | 0 | 0 | $SR(24, 0.001, 1, 0)^\dagger$ | 0.174 | 0.028 | 0.744 | 0.722 | 136 |
| Subsample 4 | 0 | 0 | $SR(24, 0.00025, 1, 0)^\ddagger$ | 0.084 | 0.077 | 0.918 | 0.890 | 197 |
| Subsample 5 | 0 | 0 | $F(3, 0.0005, 1, 0)^\S$ | 0.369 | 0.143 | 0.446 | 0.452 | 2419 |

**(b)** Sharpe ratio

| **Sample** | **$H_0$ rejected** | | **Rule with highest return** | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SSPA | stepM | Rule | $M_k^s$ (bps) | Bench (bps) | $p^{White}$ | $p^{SPA}$ | Trades |
| Subsample 1 | 31 | 0 | $F(24, 0.0005, 1, 0)^\star$ | 0.015 | 0.005 | 0.114 | 0.016 | 3370 |
| Subsample 2 | 5 | 2 | $SR^c(3, 0.005, 0, 2)$ | 0.015 | -0.002 | 0.048 | 0.000 | 2062 |
| Subsample 3 | 0 | 0 | $SR(24, 0.001, 1, 0)^\dagger$ | 0.006 | 0.001 | 0.750 | 0.566 | 136 |
| Subsample 4 | 0 | 0 | $SR(24, 0.00025, 1, 0)^\ddagger$ | 0.004 | 0.004 | 0.866 | 0.624 | 197 |
| Subsample 5 | 0 | 0 | $F(3, 0.0005, 1, 0)^\S$ | 0.011 | 0.005 | 0.504 | 0.328 | 2419 |

**(c)** Sortino ratio

| **Sample** | **$H_0$ rejected** | | **Rule with highest return** | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SSPA | stepM | Rule | $M_k^z$ (bps) | Bench (bps) | $p^{White}$ | $p^{SPA}$ | Trades |
| Subsample 1 | 32 | 2 | $BB(24, 0.25, 0, 0)$ | 0.024 | 0.007 | 0.044 | 0.002 | 11812 |
| Subsample 2 | 4 | 2 | $SR^c(3, 0.005, 0, 2)$ | 0.015 | -0.003 | 0.004 | 0.000 | 2062 |
| Subsample 3 | 0 | 0 | $SR(24, 0.001, 1, 0)^\dagger$ | 0.009 | 0.001 | 0.678 | 0.516 | 136 |
| Subsample 4 | 0 | 0 | $SR(24, 0.00025, 1, 0)^\ddagger$ | 0.006 | 0.006 | 0.812 | 0.556 | 197 |
| Subsample 5 | 0 | 0 | $F(3, 0.0005, 1, 0)^\S$ | 0.016 | 0.006 | 0.440 | 0.328 | 2419 |

$^\star F(24, 0.0005, 1, 2)$ *has equal trading signals and performance.*
$^\dagger SR(24, 0.001, 1, 2)$ *and* $SR(24, 0.001, 1, 6)$ *have equal trading signals and performance.*
$^\ddagger SR(24, 0.00025, 1, 2)$ *and* $SR(24, 0.00025, 1, 6)$ *have equal trading signals and performance.*
$^\S F(3, 0.0005, 1, 2)$ *has equal trading signals and performance.*
*The profitability and significance of the technical trading rules for the different subsamples and performance metrics at a 5% significance level. Transaction costs are set to* $g = 13$ *basis points. The* $2^{nd}$ *and* $3^{rd}$ *column of each table provide the number of significant trading rules as given by the SSPA and stepM test, respectively. The remaining 6 columns report statistics on the best-performing strategy per subperiod. The number of trades is defined as the number of switches between a long and a short position.*

Table 13 shows the performance of the best performing technical trading rules per subsample as indicated in table 12, but evaluated over the successive subperiod. When picking a trading strategy for the next subperiod, it is likely that an investor will choose the best performing trading rule over the most recent subperiod. Unfortunately, performance in the successive subperiod is substantially lower compared to the best performing trading rule in that subsample and even negative in the last subperiod. None of the strategies is included in the set of significant strategies of the successive period, e.g. the $F(24, 0.0005, 1, 0)$ is not included in the set of significant strategies of subsample 2. These results support the observation of (increased) efficiency of the cryptocurrency market. The number of trades of the strategies is comparable between both subperiods.

**Table 13:** The profitability of the best performing trading rules in the successive subsample with transaction costs

| **Sample** | **Rule with highest return in previous subperiod** | | | | |
|---|---|---|---|---|---|
| | Rule | $M_k^e$ (bps) | $M_k^e$ (bps) | $M_k^e$ (bps) | Trades |
| Subsample 1 | - | - | - | - | - |
| Subsample 2 | $F(24, 0.0005, 1, 0)$ | 0.290 | 0.008 | 0.012 | 4676 |
| Subsample 3 | $SR^c(3, 0.005, 0, 2)$ | 0.016 | 0.001 | 0.001 | 1126 |
| Subsample 4 | $SR(24, 0.001, 1, 0)$ | 0.025 | 0.001 | 0.002 | 83 |
| Subsample 5 | $SR(24, 0.00025, 1, 0)$ | -0.075 | -0.002 | -0.003 | 304 |

*The profitability the best performing technical trading rules per subsample as indicated in table 12, but evaluated over the successive subperiod. Transaction costs are set to $g = 13$ basis points. The number of trades is defined as the number of switches between a long and a short position.*

# 7 Combining Signals: A Machine Learning Approach

The previous sections reported the profitability and significance of trading signals generated from individual trading rules. Although profitable individual trading rules were identified, picking only one rule leads to loss of available information generated by the remaining strategies. Since a single trading strategy can not be expected to predict all price movements, we develop a neural network classification algorithm to combine trading signals and/or positions of multiple single trading rules into a complex trading strategy. The new combined strategies outperform the best performing individual trading rules and benchmark based on performance metrics and break-even transaction costs. Section 7.1 reviews the rationale behind combining trading signals and related academic literature. Moreover, we introduce the naive learning and voting strategies which serve as combined signal strategy benchmark. Section 7.2 discusses the implementation of the neural network algorithm. Section 7.3 interprets the profitability and significance of the developed complex trading strategies.

### 7.1 Combining Trading Signals

Single technical trading rules used in isolation will generally not be able to predict all price movements (Pring 1991). Combining trading signals and/or positions of multiple individual trading rules into complex trading strategies captures more of the available information and may provide improvements upon the single trading rules. Moreover, it reduces the risk of relying on a single strategy. As showed by Leung et al. (2000), classification models predicting the direction of the price movement appear to outperform level estimation models. Therefore we generate the new combined trading strategies by a classification algorithm, which classifies the signals and/or positions generated by the universe of trading rules into a discrete buy (1), hold (0) or sell (-1) category.

Although rarely in the literature combined trading strategies are based on discreet trading signals or positions, rather than continuous indicators, Hsu & Kuan (2005) propose three complex strategies which (naively) combine trading positions of multiple individual rules. *Learning strategies* initially select one of the component trading rules, but allows for strategy changes when one of the component trading rules is performing better, evaluated of a certain review span. *Voting strategies* use a simple average over the generated positions to determine the combined trading signal. *Fractional position strategies* adjust the invested amount based on the simple average over the trading signals, e.g. if the simple average equals 0.3, a long position of 0.3 units is taken. Although Hsu & Kuan find more significant complex trading strategies than single trading strategies, the naive combined strategies do not improve upon the single trading rules.

Subramanian et al. (2006) argue that naive combinations of single trading rules are not effective in mitigating their weaknesses, particularly in adverse market conditions. They propose a genetic algorithm which optimizes weights assigned to each trading rule in the tested universe. The agreed trading position is determined evaluating the weighted sum of all positions. The obtained optimal weights were held constant during the complete trading period. They find that their genetic program consistently improves upon single trading rules in a variety of market conditions. Similar results were reported by Briza & Naval (2011), who used particle swarm optimization to find the optimal strategy weights. Wang et al. (2014) argue that performance of a trading rule with a static choice of weights may not be persistent over time. They propose a performance-based reward algorithm which adjusts the weights based on recent performance of the component strategies. The parameters of the algorithm are optimized using time-varying particle swarm optimization. The (dynamic) algorithm outperforms all the component strategies over the complete trading period.

We use a neural network to generated combined trading signals. There exists vast literature which examines the predictability of financial time series using various types of neural networks. Early work of Tenti (1996) showed that neural networks with technical indicator input features are able to predict foreign exchange rates. Altay & Satman (2005) showed that neural networks outperform linear regression models in predicting stock market direction. As price processes are generally non-linear, neural networks have superior explanatory power due to its ability to predict complex non-linear relations. Guresen et al. (2011) provide a literature survey regarding financial time series prediction using neural networks. In this study, we will define a multiclass classification model using a neural network with trading signal and/or position vectors as input features. Section 7.2 explains neural networks and their implementation in more detail. Note that neural network setting and architecture optimization is out of the scope of this paper. The aim of this chapter is to show that neural networks can be used to combine signals. Advanced network optimization is left for further research.

Strategies similar to Hsu & Kuan (2005)'s naive learning and voting strategies are used as benchmark strategies for the neural network algorithm. The implemented learning strategies evaluate after every $m$ periods the performance of all individual trading rules over the previous $m$ periods. The investor switches between adopted trading strategy based on the best performing trading rule in the most recent evaluated period of length $m$. We denote a learning strategy with evaluation period of length $m$ by $LS(m)$. We apply three parameter settings, $m \in \{6, 12, 288\}$, implying that performance is evaluated every 30 minutes, hour or day. The voting strategies calculate the simple average $z$ over all the trading signals or positions. Trading signals determined by equation (7.1),

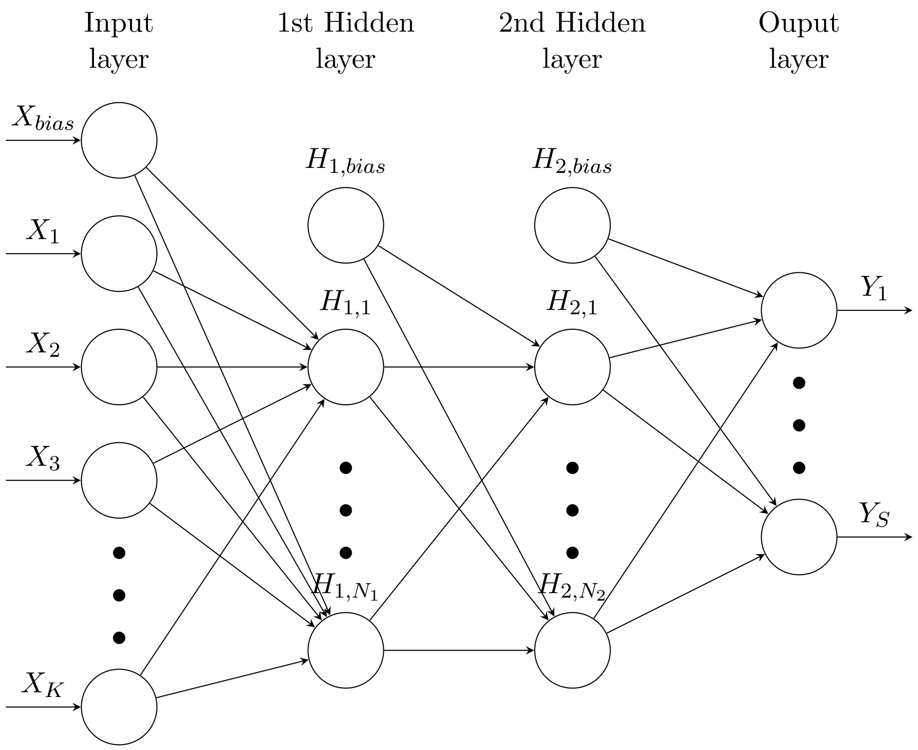
$$\begin{cases} 1 & \text{if} \quad z > b \\ 0 & \text{if else} \\ -1 & \text{if} \quad z < -b \end{cases} \tag{7.1}$$

where we set band $b \in \{0, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4\}$. Trading positions are determined buy substituting the hold (0) signals by the most recent non-zero signal. We denote a voting strategy with filter band $b$ by $VS(b)$. The voting strategies are only used as benchmark for neural networks with single trading rule classes as input feature (section 7.3.2), not for the neural networks with the complete universe of trading rules as input feature (section 7.3.1). Since the full universe consists of trend-following, trend-reversal and their contrarian trading rules, it is meaningless to take a simple average over the full universe. The strategies with a contrarian counterpart will cancel out and larger trading rule classes will dominate the simple average when evaluated over the full universe.

## 7.2 Neural Networks

Neural networks are mathematical structures, based on biological brains, consisting of interconnected nodes which interact by propagating signals of varying strength. Neural networks are used as non-linear statistical models which can be applied for both regression and classification problems. We consider the most popular form of neural networks, called feedforward networks. Figure 10 provides a schematic representation of a feedforward neural network with one input layer, two hidden layers and one output layer. The input layer represents the $K$ input variables of the network, called features, and one bias unit. The output layer represents the $S$ output classes. Each node of the hidden layers in between creates linear combinations of the preceding nodes to progressively transform the input features into the output variables. The parameters of these linear combinations, called weights, are updated during the learning process to optimally predict the output of a given sample dataset. Although the weights in each node comprise a linear combination, by combining multiple nodes and hidden layers, complex non-linear functions are constructed.

**Figure 10:** Graphical representation of a neural network




*Schematic representation of a four layered feedforward neural network with one input layer of size $k+1$, two hidden layers of size $n_1+1$ and $n_2+1$ and one output layer of size $s$.*

The neural network can be represented by the following system of equations (Friedman et al. 2001):

$$H_{1,n_1} = \sigma(\alpha_{0,n_1} + \alpha'_{n_1} X), \qquad n_1 = 1, ..., N_1 \tag{7.2}$$
$$H_{2,n_2} = \sigma(\beta_{0,n_2} + \beta'_{n_2} H_1), \qquad n_2 = 1, ..., N_2 \tag{7.3}$$
$$T_s = \gamma_{0,s} + \gamma'_s H_2, \qquad s = 1, .., S \tag{7.4}$$
$$f_s(X) = g_s(T), \qquad s = 1, .., S \tag{7.5}$$

where $\alpha, \beta$ and $\gamma$ are the weights, $\sigma$ is called the activation function and $g$ the transfer function. We follow the literature and use the hyperbolic tangent sigmoid activation function, defined by

$$\sigma(z) = \frac{2}{1 + \exp(-2z)} - 1 \tag{7.6}$$

and the softmax transfer function, defined by

$$g_s(T) = \frac{\exp(T_s)}{\sum_{i=1}^{S} (\exp(T_i))}. \tag{7.7}$$

The outputs of the softmax function are interpreted as the probability that the input vector is a member of class $s$. The corresponding classifier is defined as $C(x) = \underset{s}{argmax}[f_s(x)]$. The network weights are optimized by minimizing an error with respect to target function

$y$. As we have discreet outputs of 1 (buy), 0 (hold) or -1 (sell), we are defining a *multiclass classification* problem. The cross-entropy error function $R$ proves to be the most appropriates measure for classification problems, which is defined by

$$R(\theta) = -\sum_{i=1}^{N}\sum_{s=1}^{S} y_{i,s} \log f_s(x_i) \tag{7.8}$$

where $\theta$ is the collection of all weights, $N$ the number of observation in the training data and $y$ the target vector or matrix. The error function $R(\theta)$ is minimized using scaled conjugate gradient back-propagation, developed by Møller (1993). Similar as most minimization methods, this algorithm minimizes $R(\theta)$ by using gradient descent. The reason why we use the SCG algorithm is twofold and relies on performance of the MATLAB 'Neural Network Toolbox'. First, the SCG algorithm proves to perform well on networks with a large number of weights, both in terms of performance and speed of computation. Secondly, the memory requirements are relatively small. Both are important as we are working with a large dataset and limited computational resources. For the technical details of the SCG algorithm, we refer to Møller (1993).

The input data consists of the trading signals and/or positions generated by the trading rules divided in three sets, the training set, the validation set and the test set. We define the three sets by using the subsamples as defined in section 6.4. The training set consists of the trading signals generated during subsample 1 and 2, the validation set of the signals generated during subsample 3 and the test set of the signals generated during subsamples 4 and 5. The target vector is defined as the signs of the log returns, that is:

$$y_t = sign\left[\ln\left(\frac{p_t}{p_{t-1}}\right)\right]. \tag{7.9}$$

Since we are classifying the data in multiple categories, target vector $y_t$ has to be transformed to the appropriate form. The resulting target matrix is a $T \times S$ matrix $y$, where $y_{i,s}$ is one if the observation at time $i$ is in class $s$. All other entries are zero.

During each iteration (epoch) of the SCG algorithm, the weights of the network are optimized by minimizing $R(\theta)$ based on the training set. Moreover, after each epoch, the performance of the weights is tested out-of-sample on the validation set. Together with the training error, the validation error generally decreases during the first epochs of the training phase. When the networks starts to overfit the training data, the training error keeps decreasing, but the validation error will rise. Therefore, to avoid overfitting, the training is stopped when the validation error increases for a certain number of successive epochs. We set this number to 6, which is general practice, see footnote 26. The weights at the minimum validation error are returned as optimal weights.

The performance of the resulting trading strategy, denoted by $NN$, is evaluated on the test set only. Note however that the signals of the $NN$ strategy are transformed to positions when determining performance. That is, all periods classified as hold (0) are substituted with the most recent non-zero signal. Generally, gradient descent performs better when inputs are normalized. However, as the trading signals are already between -1 and 1, this is not necessary. As we mitigate overfitting by using a validation set, regularization is not used. For further details on neural networks and there applications, we refer to Friedman et al. (2001).

### 7.3 Significance of the Combined Signal Strategies

Combining trading signals of individual technical trading rules by means of a neural network results in strategies which outperform the individual trading rules and naive learning and voting strategies. Section 7.3.1 reports the results of a combined signal strategy generated by a neural network with trading signals of the full universe of trading rules as input features. The resulting strategies outperform the individual strategies and benchmarks. The constructed network is kept small to ensure feasible computation time with the limited resources we have. Section 7.3.2 examines the classes of trading rules individually. Since these input datasets are smaller, we are able to include additional input features. The resulting strategies outperform the best component for most trading rule classes.

#### 7.3.1 Network of the Full Universe of Trading Rules

The universe of technical trading rules consists of 3312 strategies. However, as the contrarian rules generate opposite signals compared to the standard strategies, negative weights of the network automatically include these strategies already. Moreover, strategies which generate duplicate trading signals are removed from the dataset. The resulting vector of input features $X$ consists of $K = 1593$ trading rules and one bias unit. The constructed neural network consists of two hidden layers, hidden layer $H_1$ containing $N_1 = 20$ neurons and hidden layer $H_2$ containing of $N_2 = 5$ neurons. Both hidden layers have one additional bias unit. The output layer $Y$ consists of $S = 3$ neurons, representing the long (1), hold (0) and short (-1) category. In determining the architecture of the network we searched for a balance between computation time and flexibility to capture non-linearities in the data.[26] Transaction costs are excluded, but break-even transaction costs are reported instead. Network training is repeated multiple times, with random starting weights, to avoid ending up in a local minimum (Yao et al. 2001). The optimal run is determined based of network performance on the validation set.

We developed two different combined signal strategies, differentiated by the input features of the neural network. The most natural input features are the trading positions $s_{t,k}$ of the individual strategies. The combined signal strategy resulting from this network is denoted by $NN^{pos}$. However, the trading position of the strategy might not always be an appropriate representation of the information generated by the trading rule. If no trading signal is generated, the position of the strategy is based on the previous position and contains different information then the position that was taken directly after a trade. For example, prices increased and a support and resistance strategy generated a buy signal at $t = 1$. However, prices remain flat thereafter and as a result no other trades occur until $t = T$. The strategy's position vector will consists solely of ones as the long position is held until $t = T$, while the signal vector has a one at the first cell and zeros thereafter. The information contained in these vectors is different and might be appropriate in different situations. Therefore we define a combined signal strategy based on trading signals as input features as well, denoted by $NN^{sig}$. Note that the positions of the resulting combined strategies remain to consists solely of long and short positions. The periods classified as a hold (0) signal are substituted with the most recent non-zero signal when transforming the fitted vector to strategy positions.

Based on this two combined signal strategies, we develop an additional four strategies differentiated by different target vectors $y$ as input variable. The target vector as defined

[26] An experienced high-frequency trading practitioner with daily exposure to machine learning algorithms advised us on the architecture of the model, based on the size of the dataset, our computational resources and the scope of the paper.

in (7.9) classifies observations based on the sign of the returns. However, even if the return is negligibly small, the observation will be classified as a buy (1) or sell (-1) signal. But when transaction costs are present, it may be suboptimal to switch position based on such small returns, and holding the current position leads to better performance. Therefore a target vector is defined where all returns within a band of $b_y$ basis points are treated as hold (0) observations. We set $b_y = 13$ and $b_y = 26$ basis points for both the $NN^{pos}$ and $NN^{sig}$ strategy, resulting in four additional strategies, denoted by $NN^{\cdot,13}$ and $NN^{\cdot,26}$. The size of the bandwidth is related to the one-way transaction costs as described in section 6.3. When $b_y = 26$ basis points, all returns below the transaction costs are classified as a hold signal in the target vector. The rationale is that one only changes position when next period's expected return exceeds the transaction costs and is undoubtedly profitable. The resulting target vector has around 100 000 observations classified as non-hold. However, we are aware that this might not always be appropriate. After all, successive periods with positive returns below the transaction costs can be profitable if a long position in taken during the first period and no further trades are executed thereafter. Therefore, we test the combined signal strategies for $b_y = 13$ basis points as well. The resulting target vector has around 200 000 observations classified as non-hold. Considering the high volatility and kurtosis of the returns, it is unlikely that returns have the same sign for long consecutive periods and therefore we do not test for smaller levels of $b_y$.

Table 14 reports the performance metrics, number of trades and break-even transaction costs of the combined signals strategies. For comparison, the performance of the individual trading rule with the highest Sharpe ratio, $B(4, 0.25, 0, 0)$, and the return of the buy-and-hold benchmark, both evaluated over subsamples 4 and 5, is reported in the table as well. Moreover, the performance of the best performing naive learning strategy benchmark, $LS(288)$, is reported as well. The $NN^{pos}$, $NN^{sig}$ and $NN^{sig,13}$ strategies outperform the best individual strategy and both benchmarks on all performance metrics ánd break-even transaction costs. Hence, it is concluded that combining signals of individual strategies by means of a neural network yields superior performance. Since the $NN^{sig,13}$ trading rule has break-even transaction costs exceeding 13 basis points, the presence of transaction costs does not necessarily eliminate the strategy's profitability. The $NN^{sig,13}$ strategy correctly classifies 68% of the price movements in the test set (out-of-sample). Interestingly, the input feature which has the largest sum of absolute weights in the first hidden layer of the $NN^{sig,13}$ network is the $B(4, 0.25, 0, 0)$ strategy. Hence, the strategy which passes most information through the network is indeed the best performing trading rule as indicated in section 6.2.[27] It is observed that the $NN^{\cdot,sig}$ strategies perform consistently superior compared to the $NN^{\cdot,pos}$ strategies, not only based on performance metrics, but also on percentage correct classification and break-even transaction costs. Table 15 reports return statistics of the $NN^{sig,13}$ trading rule. As the $NN$ strategies improve upon the individual trading rules and benchmarks, their significance is evident and requires no further testing. The best performing learning strategy is the $LS(288)$ trading rule. Although the break-even transaction costs of the trading rule are higher compared to the $B(4, 0.25, 0, 0)$ strategy, it does not outperform the best individual trading rule based on performance metrics. Note that the neural network automatically includes the contrarian counterpart of every trading rule by allowing negative weights in the network. Therefore, in order to make the benchmark comparable to the $NN$ strategies, the learning strategies are calculated by including the contrarian trading rules of all classes in the universe. As stated above, the voting strategies are used as benchmarks in the next section only.

[27]Due to the size of the network and the multiple hidden layers, further meaningful interpretation of the network weights is not possible.

**Table 14:** Performance of the combined signal strategies and benchmarks over the test set using the full universe of trading rules as input features

| Trading rule | Performance metrics (bps) | | | Cor. class. | Trades | |
|---|---|---|---|---|---|---|
| | $M^e$ | $M^s$ | $M^z$ | | Trades | BETC |
| $NN^{pos}$ | 2.712 | 0.112 | 0.167 | 51.6% | 45 526 | 5.02 |
| $NN^{sig}$ | 7.688 | 0.332 | 0.672 | 64.3% | 83 705 | 7.56 |
| $NN^{pos,13}$ | 0.300 | 0.012 | 0.017 | 64.5% | 2959 | 10.95 |
| $NN^{sig,13}$ | 3.750 | 0.155 | 0.274 | 68.0% | 20 180 | 15.49 |
| $NN^{pos,26}$ | -0.200 | -0.008 | -0.012 | 85.3% | 0 | - |
| $NN^{sig,26}$ | 1.211 | 0.050 | 0.075 | 85.3% | 4456 | 23.89 |
| $B(4, 0.25, 0, 0)$ | 2.639 | 0.109 | 0.163 | - | 52 995 | 4.20 |
| $LS(288)$ | 2.529 | 0.104 | 0.155 | - | 25 815 | 8.27 |
| Benchmark $r_0$ | 0.100 | 0.004 | 0.006 | - | - | - |

*Performance of the combined signal strategies using the full universe of trading rules as input features for the four layered feedforward neural network. For comparison, the best performing individual trading rule, evaluated of subsamples 4 and 5, the return benchmark and the best learning strategy are given as well. The $2^{nd}$ till $4^{th}$ column report the performance metrics. The $5^{th}$ column reports the percentage of correctly classified price movements within the test set. The $6^{th}$ and $7^{th}$ column provide the number of trades and break-even transaction costs.*

**Table 15:** Return statistics of the $NN^{sig,13}$ strategy over subsamples 4 and 5

| | |
|---|---|
| Mean excess log returns $M_k^e$ (bps) | 3.750 |
| Standard deviation (bps) | 33.2 |
| Minimum (bps) | $-1064.6$ |
| Maximum (bps) | 3107.6 |
| Skewness | 8.92 |
| Kurtosis | 609.5 |
| Maximum drawdown (bps) | 1118.0 |
| Number of profitable trades | 13 451 |
| Number of losing trades | 6693 |
| Number of zero-return trades | 36 |
| Mean return of profitable trades (bps) | 63.506 |
| Mean return of losing trades (bps) | -36.615 |

*Descriptive statistic of the returns (excess of the buy-and-hold benchmark) of the $NN^{sig,13}$ strategy over subsamples 4 and 5. The return of a trade is defined as the sum of log returns obtained during a period in which the same position is maintained.*

### 7.3.2 Network of Trading Rules Classes

This section examines the classes of trading rules individually, by training neural networks with input features from single trading rule classes. In this way we can study whether the combined signal strategies outperform their best performing component within each class of trading rules. Similar as previously, the constructed neural networks consist of two hidden layers, with 20 and 5 neurons respectively. We add one additional type of combined signal strategy, $NN^{both}$, where both the trading positions and signals are included as input features. Similar as above, band $b_y$ is included to define different target vectors $y$.

Table 16 reports the Sharpe ratio and break-even transaction costs of the combined signals strategies of the individual trading rule classes. Moreover, the best component, naive learning and voting strategy are reported as benchmarks. It is concluded that for most of the classes of trading rules it holds that all benchmarks are outperformed when combining the information generated by the included trading rules by means of a neural network. Moreover, some combined signal strategies yield break-even transaction costs exceeding 13 bps, hence the presence of transaction costs does not necessarily eliminate profitability. It is observed that the $NN^{sig}$ strategies outperform the $NN^{pos}$ strategies. Furthermore, the $NN^{both}$ strategies seem to outperform the $NN^{sig}$ strategies, but this is not consistent over all classes and strategies. None of the strategies is able to outperform the neural network which includes the full universe of trading rules. Note that the strategies with (-) break-even transaction costs make 1 or less trades during subsample 4 and 5. Such strategies with 0.000 Sharpe ratio are long and strategies with -0.008 Sharpe ratio are short during the complete sample period. Moreover, note that neural networks include the contrarian counterpart of each trading rule by allowing for negative network weights. Hence, when evaluating the benchmarks, all contrarian strategies are included, even if these strategies are not included in the universe defined in section 2. The naive learning strategies are not able to outperform the best component of each class of trading rule. However, some naive voting strategies slightly outperform the best component trading rule. It is observed that for all trading classes the voting strategy with $b = 0$ performs best. These strategies trade most frequent since no hold signals are generated when $b = 0$.

**Table 16:** Performance of the combined signal strategies and benchmarks over the test set using the trading rules classes as input features

| **Trading rule** | **Performance**: $M^s$ (BETC) | | | | | | |
|---|---|---|---|---|---|---|---|
| | F | MA | SR | CB | RSI | OBV | BB |
| $NN^{pos}$ | 0.090 (4.50) | 0.012 (1.82) | 0.024 (4.06) | 0.038 (3.73) | 0.126 (4.03) | 0.000 (-) | 0.104 (4.92) |
| $NN^{sig}$ | 0.157 (3.78) | 0.072 (2.16) | 0.098 (3.64) | 0.051 (2.28) | 0.102 (2.37) | 0.000 (-) | 0.194 (4.16) |
| $NN^{both}$ | 0.210 (6.09) | 0.029 (2.87) | 0.058 (3.90) | 0.043 (3.95) | 0.184 (4.69) | 0.000 (-) | 0.212 (5.49) |
| $NN^{pos,13}$ | 0.003 (10.67) | 0.000 (-) | 0.002 (110.31) | 0.003 (18.20) | -0.008 (-) | 0.000 (-) | 0.015 (8.46) |
| $NN^{sig,13}$ | 0.059 (13.06) | 0.000 (-) | 0.019 (13.24) | 0.004 (13.41) | -0.008 (-) | 0.000 (-) | 0.032 (11.42) |
| $NN^{both,13}$ | 0.054 (13.27) | 0.005 (11.75) | 0.000 (-) | 0.001 (21.65) | 0.002 (10.06) | 0.000 (-) | 0.055 (10.44) |
| $NN^{pos,26}$ | 0.001 (21.70) | 0.000 (-) | 0.000 (-) | 0.000 (-) | -0.004 (-) | 0.000 (-) | 0.000 (-) |
| $NN^{sig,26}$ | 0.006 (26.75) | 0.000 (-) | 0.000 (-) | -0.008 (-) | -0.008 (-) | 0.000 (-) | 0.000 (-) |
| $NN^{both,26}$ | 0.011 (20.96) | 0.008 (-) | 0.000 (-) | 0.000 (-) | -0.008 (-) | 0.000 (-) | 0.004 (17.02) |
| Best component | 0.099 (5.20) | 0.057 (4.13) | 0.062 (4.15) | 0.061 (4.12) | 0.059 (2.89) | 0.000 (-) | 0.109 (4.20) |
| Best $LS(m)$ | 0.072 (5.85) | 0.033 (2.88) | 0.051 (4.20) | 0.050 (4.16) | 0.058 (4.72) | 0.000 (-) | 0.092 (7.34) |
| Best $VS^{pos}(b)$ | 0.011 (1.91) | 0.004 (3.02) | 0.006 (3.65) | 0.024 (5.17) | -0.001 (-) | 0.000 (-) | 0.022 (3.17) |
| Best $VS^{sig}(b)$ | 0.100 (2.74) | 0.039 (3.60) | 0.067 (4.15) | 0.066 (4.12) | 0.052 (2.14) | 0.000 (-) | 0.095 (3.14) |

*Sharpe ratio and break-even transaction costs of the combined signal strategies using the individual trading rule classes as input features for the four layered feedforward neural network. For comparison, the best performing individual trading rule, learning and voting strategy within each class of trading rules, evaluated of subsamples 4 and 5, is given as well.*

# 8 Conclusion

This paper examines and confirms the profitability of technical analysis in the cryptocurrency market. There exist vast literature regarding the widespread use and significant excess profitability of technical trading rules in the foreign exchange market. However, this is the first paper which studies technical analysis in the *cryptocurrency* market. We examine performance of a large universe of technical trading rules on the 5-minute BTC/USD spot exchange rate between 2013 and 2017. Data-snooping effects are mitigated by using White's Reality Check, the SPA test, the stepM test and the SSPA test.

Technical trading rules have predictive power in the cryptocurrency market and transaction costs do not necessarily eliminate excess profitably. Both the stepM and SSPA test indicate numerous significant trading strategies, evaluated over the full sample period, even when realistic transaction costs are present. Both White's Reality Check and the SPA test report that the best performing trading strategy is highly significant. Nevertheless, the profitability of the trading strategies seems to decline sharply over time. In fact, none of the trading rules is significantly profitable after 2014. This may serve as evidence that the cryptocurrency market has become more efficient over time.

Although profitable individual trading rules were identified, individual technical trading rules used in isolation will generally not be able to predict all price movements. Since picking only one rule leads to lose of available information generated by the remaining strategies, we develop a neural network classification algorithm which combines trading signals or positions of multiple individual trading rules into a complex trading strategy. The new combined strategies outperform the best performing individual trading rules and benchmarks based on performance metrics and break-even transaction costs. Since these significantly profitable trading strategies with realistic break-even transaction costs exists, it is concluded that the cryptocurrency market is not fully efficient.

# 9 Discussion and Further Research

This section discusses some of the important decisions made in conducting the research and writing this paper. We highlight potential extensions of this study and propose some interesting related topics for further research.

The design of the universe of trading rules has major influence of the results. Many classes of technical trading rules and different parameterizations exists, but little guidance on profitability and trading rule selection is available (Park et al. 2016). Particularly, as trading rules at a 5-minute frequency are rarely discussed in the literature, determining reasonable parameterizations of the trading strategies is challenging. We based the parameterizations of the trading rules on works of Scholtus & van Dijk (2012) and Hudson et al. (2017), but whether these setting are actually used by practitioners is unclear. The low trading frequency of the on-balance volume average trading rules might indicate that we have chosen inappropriate parameters for this trading class. Another approach is to set the parameters such that the trading rules cover a large surface in the parameterization space, without considering the actual use by practitioners. For example, Sobol sequences (Sobol & Levitan 1976), might be an appropriate method to choose parameter settings. Optimization of trading rule parameterization might serve as an interesting topic for further research. Expanding the universe of trading rules is also a frequently used method to extend existing research. As cryptocurrencies are not related to countries with certain timezones, examining the prevalence of existing (intra-day) calender effects might be of interest.

Some technical trading rules turn out to be highly profitable, even after transaction costs. As reported in section 6.3, the 5-minute mean excess log return of the best performing trading rule with transaction costs equals 0.379 basis points. This return seems unrealistically high, but can be explained by the high volatility of the BitCoin price and the high trading frequency of the trading strategies. Although, potential short-sale restrictions, limited liquidity and other market restrictions might influence the profitability. What we did not consider in the paper is the possible impact of the bid-ask bounce on these high returns. Unfortunately, order book and bid-ask spread data was not available. Examining the impact of the bid-ask bounce bias on the profitability of the trading rules might be an interesting topic for further research.

As discussed in section 7.1, neural network setting optimization is out of scope of this study and left for further research. Besides improving the neural network settings and architecture, another way to extend the paper is to add additional input features. Interesting possibilities are information on different cryptocurrencies than BitCoin, information of stocks of technological companies acting in the field of digital payments and blockchain, or the number of news articles and Google searches related to BitCoin. We are aware that the neural network trained in this paper includes contrarian strategies of trading classes for which we argued in section 2 that no reasonable rationale exists. Other machine learning techniques were considered, but based on the size of the dataset and required computation time is was concluded that neural networks are the most appropriate algorithm. A disadvantage of the neural network algorithm is that the component weights are static. Constructing a dynamic performance-based machine learning algorithm might be an interesting topic for further research.

At the end of December 2017, CBOE Global Market and CME Group launched the first BitCoin futures contracts. These BitCoin derivatives are traded on regulated markets, attracting more investors. The existence of BitCoin derivatives will open many new fields of interesting financial research regarding cryptocurrencies. An interesting advantage of derivative contracts is that transaction costs are generally lower compared to normal trades. Hence, research on technical trading of derivative contracts might be an interesting topic for further research, both for practitioners and academics.

# A Appendices

## A.1 Trading Rule Parameterizations

The parameterizations of the trading rules are primarily based on Scholtus & van Dijk (2012), who evaluate trading rule performance for time intervals of 30 seconds, 60 seconds and 5 minutes and Hudson et al. (2017) who evaluate technical trading rules for 5- to 60-min time intervals. The parameterizations are given in table 17. The total number of trading rules is given by

$$(225 + 396 + 270 + 360 + 180 + 495 + 180) + (396 + 270 + 260 + 180) = 3312. \tag{A.1}$$

**Table 17:** Trading rule parameterizations

| Trading rule | Parameters | Description | Values |
|---|---|---|---|
| F | $x$ | Threshold for long/short signal | $0.0005, 0.001, 0.0025, 0.005, 0.01$ |
| (225) | $e$ | Length of time interval for alternative extrema | $-, 3, 6, 12, 24$ |
| | $d$ | Time delay filter | $0, 1, 3$ |
| | $c$ | Holding period | $0, 2, 6$ |
| MA | $q$ | Length of short-run moving average | $2, 4, 6, 8$ |
| (396) | $j$ | Length of long-run moving average | $4, 6, 12, 24$ |
| | $b$ | Threshold for long/short signal | $0.0005, 0.001, 0.005, 0.01$ |
| | $d$ | Time delay filter | $0, 1, 3$ |
| | $c$ | Holding period | $0, 2, 6$ |
| SR | $n$ | Evaluated time intervals | $3, 6, 12, 24, 36$ |
| (270) | $b$ | Threshold for long/short signal | $0, 0.00025, 0.0005, 0.001, 0.0025, 0.005$ |
| | $d$ | Time delay filter | $0, 1, 3$ |
| | $c$ | Holding period | $0, 2, 6$ |
| CB | $n$ | Evaluated time intervals | $3, 6, 12, 24, 36$ |
| (360) | $x$ | Maximum bandwidth to form a channel | $0.005, 0.01, 0.02, 0.03$ |
| | $b$ | Threshold for long/short signal | $0, 0.0001, 0.00025, 0.0005, 0.001, 0.002$ |
| | $c$ | Holding period | $0, 2, 6$ |
| RSI | $m$ | Evaluated time intervals | $3, 4, 6, 12, 24$ |
| (180) | $v$ | Threshold for long/short signal | $10, 20, 30, 40$ |
| | $d$ | Time delay filter | $0, 1, 3$ |
| | $c$ | Holding period | $0, 2, 6$ |
| OBV | $q$ | Length of short-run moving average | $2, 4, 6, 8$ |
| (495) | $j$ | Length of long-run moving average | $4, 6, 12, 24$ |
| | $b$ | Threshold for long/short signal | $0.05, 0.1, 0.25, 0.5, 1$ |
| | $d$ | Time delay filter | $0, 1, 3$ |
| | $c$ | Holding period | $0, 2, 6$ |
| BB | $j$ | Length of moving average and volatility | $3, 4, 6, 12, 24$ |
| (180) | $k$ | Bandwidth; number of standard deviations | $0.25, 0.5, 1, 2$ |
| | $d$ | Time delay filter | $0, 1, 3$ |
| | $c$ | Holding period | $0, 2, 6$ |

*Technical trading rule parameters. The set of trading rules consists of filter (F), moving average (MA), support and resistance (SR), channel breakouts (CB), relative strength indicator (RSI), on-balance volume average (OBV) and bollinger band (BB) rules. The number of standard trading rules within each type is given below the abbreviation.*

## A.2 Tables

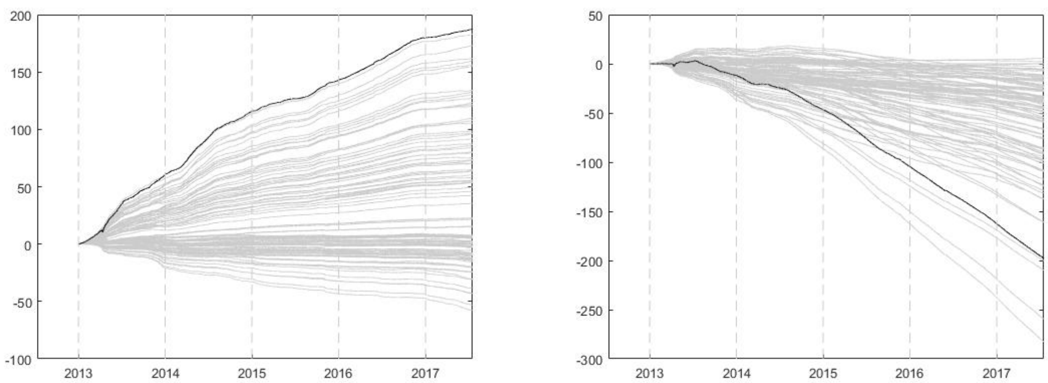
**Table 18:** Fee schedule BitStamp exchange

| 30-day volume (USD) | Fee |
|---|---|
| < 20.000 | 0.25% |
| < 100.000 | 0.24% |
| < 200.000 | 0.22% |
| < 400.000 | 0.20% |
| < 600.000 | 0.15% |
| < 1.000.000 | 0.14% |
| < 2.000.000 | 0.13% |
| < 4.000.000 | 0.12% |
| < 20.000.000 | 0.11% |
| > 20.000.000 | 0.10% |

*The transaction cost schedule applicable for the BitStamp exchange.*

## A.3 Figures

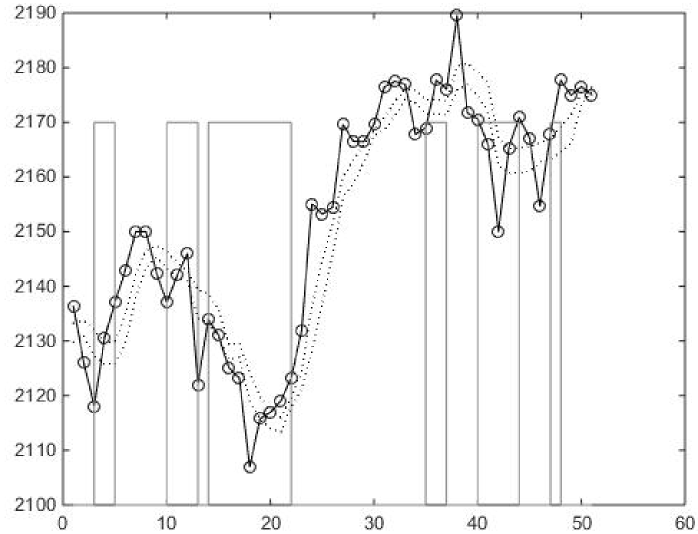
**Figure 11:** Cumulative log returns of the bollinger band trading rules




**(a)** Excluding transaction costs **(b)** Including transaction costs

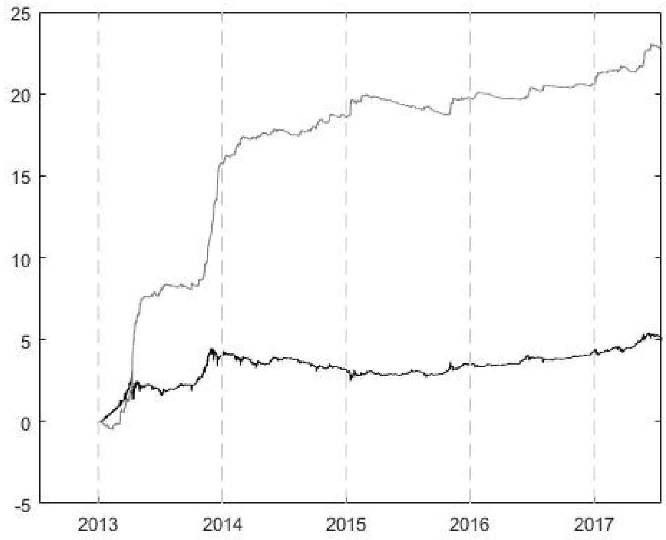
*Figure 11a shows cumulative log returns of all bollinger band trading rules over the full sample period without transaction costs. Interestingly, the returns seem to cross only rarely. Figure 11b shows cumulative log returns of all bollinger band trading rules over the full sample period including transaction costs of* $g = 13$ *basis points. The dark line is the* $BB(4, 0.25, 0, 0)$ *strategy.*

**Figure 12:** Trading signals of $BB(4, 0.25, 0, 0)$




*Trading signals of the bollinger band $BB(4, 0.25, 0, 0)$ strategy over a focused period of 50 time intervals. The black line represents the exchange rate $p_t$. The dotted lines are the bollinger bands determined as $k = 0.25$ times the moving standard deviation distance from the moving average. The blocks represent the periods in which the strategy takes a long position in the foreign currency.*

**Figure 13:** Cumulative returns of the filter $F(3, 0.001, 1, 0)$ strategy with transaction costs.




*Cumulative excess log returns of the filter $F(3, 0.001, 1, 0)$ strategy over the full sample period with transaction costs. The dark line represents excess log return of the $F(3, 0.001, 1, 0)$ strategy, the gray line the buy-and-hold benchmark.*

**Table 19:** Descriptive statistics of BitCoin prices, volume and returns based on 5-min data

| | | **Volume** (₿) | | **Prices** ($) | | | | **5-min log returns** ($) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Year | 5-min intervals | Volume | Trades | Mean | SD | Min | Max | Mean (bps) | SD (bps) | Skew | Kurt | Min | Max | ADF | LBQ |
| 2011 | 31 514 | 7793 | 604 | 3.8 | 1.1 | 2.2 | 15.0 | −0.085 | 141.4 | −36.41 | 8796 | −1.71 | 1.23 | −178* | 7 |
| 2012 | 105 408 | 567 949 | 73 081 | 8.2 | 3.1 | 3.8 | 16.4 | 0.101 | 52.2 | 2.99 | 1127 | −0.38 | 0.46 | −354* | 1301* |
| 2013 | 105 120 | 5 031 147 | 2 148 708 | 187.5 | 242.2 | 12.8 | 1163.0 | 0.382 | 77.0 | 4.21 | 569 | −0.37 | 0.61 | −346* | 1876* |
| 2014 | 105 120 | 5 024 184 | 3 587 679 | 525.5 | 143.6 | 275.0 | 995.0 | −0.078 | 34.8 | 0.21 | 60 | −0.09 | 0.15 | −383* | 3138* |
| 2015 | 105 120 | 5 525 311 | 2 737 900 | 272.3 | 59.0 | 152.4 | 502.0 | 0.028 | 28.3 | −4.82 | 387 | −0.21 | 0.09 | −366* | 2381* |
| 2016 | 105 408 | 1 992 263 | 1 692 727 | 565.8 | 137.4 | 352.0 | 980.7 | 0.077 | 18.9 | −0.74 | 68 | −0.06 | 0.08 | −402* | 4836* |
| 2017 | 57 005 | 2 156 812 | 2 207 494 | 1548.7 | 648.9 | 751.3 | 2980.0 | 0.142 | 32.3 | −2.83 | 139 | −0.16 | 0.07 | −263* | 735* |

** significance at a 1% level.*

*Descriptive statistics on volume, prices and 5-minute log returns of the USD/BTC exchange rate traded on the Bitstamp exchange. As the dataset starts at 03-09-2011 and ends at 17-07-2017, the descriptive statistics for 2011 and 2017 are determined over a shorter period. Standard deviation is abbreviated as 'SD', Augmented Dickey-Fuller as 'ADF' and Ljung-box Q as 'LBQ'.*

# B Bibliography


Alexander, S. S. (1961), 'Price movements in speculative markets: Trends or random walks', *Industrial Management Review* **2**(2), 7.

Altay, E. & Satman, M. H. (2005), 'Stock market forecasting: artificial neural network and linear regression comparison in an emerging market', *Journal of Financial Management & Analysis* **18**(2), 18–33.

Angel, J. & McCabe, D. (2015), 'The ethics of payments: Paper, plastic, or bitcoin?', *Journal of Business Ethics* **132**(3), 603–611.

Bajgrowicz, P. & Scaillet, O. (2012), 'Technical trading revisited: False discoveries, persistence tests, and transaction costs', *Journal of Financial Economics* **106**(3), 473–491.

Balcilar, M., Bouri, E., Gupta, R. & Roubaud, D. (2017), 'Can volume predict bitcoin returns and volatility? a quantiles-based approach', *Economic Modelling* **64**, 74–81.

Balsara, N., Chen, J. & Zheng, L. (2009), 'Profiting from a contrarian application of technical trading rules in the us stock market', *Journal of Asset Management* **10**(2), 97–123.

Barras, L., Scaillet, O. & Wermers, R. (2010), 'False discoveries in mutual fund performance: Measuring luck in estimated alphas', *Journal of Finance* **65**(1), 179–216.

Benjamini, Y. & Hochberg, Y. (1995), 'Controlling the false discovery rate: a practical and powerful approach to multiple testing', *Journal of the royal statistical society. Series B (Methodological)* pp. 289–300.

Bollinger, J. (1992), 'Using bollinger bands', *Stocks & Commodities* **10**(2), 47–51.

Bouri, E., MolnÃ¡r, P., Azzi, G., Roubaud, D. & Hagfors, L. I. (2017), 'On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier?', *Finance Research Letters* **20**(C), 192–198.

Briere, M., Oosterlinck, K. & Szafarz, A. (2015), Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoins, Technical Report 6.

Briza, A. C. & Naval, P. C. (2011), 'Stock trading system based on the multi-objective particle swarm optimization of technical indicators on end-of-day market data', *Applied Soft Computing* **11**(1), 1191 – 1201.

Brock, W., Lakonishok, J. & LeBaron, B. (1992), 'Simple technical trading rules and the stochastic properties of stock returns', *The Journal of finance* **47**(5), 1731–1764.

Chen, T., Robertson, B., Gao, G., Chen, L. Y. & Nakamura, Y. (2017), 'High-Speed Traders Are Taking Over Bitcoin'. [Bloomberg News, Posted on 16-January-2017].
**URL:** *https://www.bloomberg.com/news/articles/2017-01-16/high-speed-traders-are-taking-over-bitcoin-as-easy-money-beckons*

Cheung, Y. & Chinn, M. (2001), 'Currency traders and exchange rate dynamics: a survey of the US market', *Journal of International Money and Finance* **20**(4), 439–471.

Cheung, Y., Chinn, M. & Marsh, I. (2004), 'How Do UK-Based Foreign Exchange Dealers Think Their Market Operates?', *International Journal of Finance and Economics* **9**, 289–306.

Cheung, Y. & Wong, C. (2000), 'A survey of market practitioners' views on exchange rate dynamics', *Journal of International Economics* **51**(2), 401–419.

Chicaroli, R. & Pereira, P. L. V. (2015), 'Predictability of Equity Models', *Journal of Forecasting* **34**(6), 427–440.

Coakley, J., Marzano, M. & Nankervis, J. (2016), 'How profitable are FX technical trading rules?', *International Review of Financial Analysis* **45**, 273–282.

Cornell, W. B. & Dietrich, J. K. (1978), 'The Efficiency of the Market for Foreign Exchange under Floating Exchange Rates', *The Review of Economics and Statistics* **60**(1), 111–120.

Curcio, R., Goodhart, C., Guillaume, D. & Payne, R. (1997), 'Do Technical Trading Rules Generate Profits? Conclusions from the Intra-day Foreign Exchange Market', *International Journal of Finance & Economics* **2**(4), 267–280.

Diebold, F. & Mariano, R. (1995), 'Comparing predictive accuracy', *Journal of Business & Economic Statistics* **13**(3), 253–63.

Donchian, R. D. (1960), 'Commodities: High finance in copper', *Financial Analysts Journal* **16**(6), 133–142.

Dooley, M. & Schafer, J. (1983), 'Analysis of Short-Run Exchange Rate Behaviour: March 1973 to November 1981', *Exchange rate and trade instability* pp. 43–69.

Dueker, M. & Neely, C. J. (2007), 'Can Markov switching models predict excess foreign exchange returns?', *Journal of Banking & Finance* **31**(2), 279–296.

Dwyer, G. P. (2015), 'The economics of Bitcoin and similar private digital currencies', *Journal of Financial Stability* **17**, 81–91.

Eross, A., Urquhart, A., McGroarty, F. & Wolfe, S. (2017), 'The intraday dynamics of bitcoin', *Working Paper Heriot-Watt University* .

Fama, E. F. (1970), 'Efficient Capital Markets: A Review of Theory and Empirical Work', *Journal of Finance* **25**(2), 383–417.

Fama, E. F. & Blume, M. E. (1966), 'Filter rules and stock-market trading', *The Journal of Business* **39**(1), 226–241.

Fama, E. F. & French, K. R. (2012), 'Size, value, and momentum in international stock returns', *Journal of Financial Economics* **105**(3), 457–472.

Friedman, J., Hastie, T. & Tibshirani, R. (2001), *The elements of statistical learning*, Vol. 1, Springer series in statistics New York.

Frömmel, M. & Lampaert, K. (2016), 'Does frequency matter for intraday technical trading?', *Finance Research Letters* **18**, 177–183.

Gartley, H. M. (1935), *Profits in the stock market*, Health Research Books.

Gehrig, T. & Menkhoff, L. (2004), 'The use of flow analysis in foreign exchange: exploratory evidence', *Journal of International Money and Finance* **23**(4), 573–594.

Gençay, R., Ballocchi, G., Dacorogna, M., Olsen, R. & Pictet, O. (2002), 'Real-Time Trading Models and the Statistical Properties of Foreign Exchange Rates', *International Economic Review* **43**(2), 463–492.

Granville, J. E. (1963), *New key to stock market profits*, Prentice-Hall.

Guresen, E., Kayakutlu, G. & Daim, T. U. (2011), 'Using artificial neural network models in stock market index prediction', *Expert Systems with Applications* **38**(8), 10389–10397.

Hansen, P. (2005), 'A test for superior predictive ability', *Journal of Business & Economic Statistics* **23**, 365–380.

Hansen, P. R., Lunde, A. & Nason, J. M. (2011), 'The model confidence set', *Econometrica* **79**(2), 453–497.

Hsu, P.-H., Hsu, Y.-C. & Kuan, C.-M. (2010), 'Testing the predictive ability of technical analysis using a new stepwise test without data snooping bias', *Journal of Empirical Finance* **17**(3), 471–484.

Hsu, P.-H. & Kuan, C.-M. (2005), 'Reexamining the profitability of technical analysis with data snooping checks', *Journal of Financial Econometrics* **3**(4), 606–628.

Hsu, P.-H., Taylor, M. P. & Wang, Z. (2016), 'Technical trading: Is it still beating the foreign exchange market?', *Journal of International Economics* **102**, 188–208.

Hudson, R., McGroarty, F. & Urquhart, A. (2017), 'Sampling frequency and the performance of different types of technical trading rules', *Finance Research Letters* **22**(C), 136–139.

Jegadeesh, N. & Titman, S. (1993), 'Returns to buying winners and selling losers: Implications for stock market efficiency', *Journal of Finance* **48**(1), 65–91.

Jensen, M. & Bennington, G. A. (1970), 'Random walks and technical theories: Some additional evidence', *Journal of Finance* **25**(2), 469–82.

Karpoff, J. (1987), 'The relation between price changes and trading volume: A survey', *Journal of Financial and Quantitative Analysis* **22**(01), 109–126.

Kim, T. (2017), 'On the transaction cost of bitcoin', *Finance Research Letters* **23**(Supplement C), 300 – 305.

Kleinbrod, V. M. & Li, X.-M. (2017), 'Order flow and exchange rate comovement', *Journal of International Money and Finance* **77**, 199–215.

LeBaron, B. (1999), 'Technical trading rule profitability and foreign exchange intervention', *Journal of International Economics* **49**(1), 125–143.

LeBaron, B. (2000), 'Technical trading profitability in foreign exchange markets in the 1990's', *Unpublished* .

Lee, C. I. & Mathur, I. (1996), 'Trading rule profits in european currency spot cross-rates', *Journal of Banking & Finance* **20**(5), 949–962.

Leung, M. T., Daouk, H. & Chen, A.-S. (2000), 'Forecasting stock indices: a comparison of classification and level estimation models', *International Journal of Forecasting* **16**(2), 173–190.

Levich, R. M. & Thomas, L. (1993), 'The significance of technical trading-rule profits in the foreign exchange market: a bootstrap approach', *Journal of International Money and Finance* **12**(5), 451–474.

Levy, R. A. (1967), 'Relative Strength As A Criterion For Investment Selection', *Journal of Finance* **22**(4), 595–610.

Lo, A. & MacKinlay, A. C. (1990), 'Data-snooping biases in tests of financial asset pricing models', *Review of Financial Studies* **3**(3), 431–67.

Loque, D., Sweeney, R. & Willett, T. (1978), 'Speculative behavior of foreign exchange rates during the current float', *Journal of Business Research* **6**(2), 159–174.

Lui, Y. & Mole, D. (1998), 'The use of fundamental and technical analyses by foreign exchange dealers: Hong Kong evidence', *Journal of International Money and Finance* **17**(3), 535–545.

Lunde, A. & Hansen, P. R. (2005), 'A forecast comparison of volatility models: does anything beat a GARCH(1,1)?', *Journal of Applied Econometrics* **20**(7), 873–889.

Manahov, V., Hudson, R. & Gebka, B. (2014), 'Does high frequency trading affect technical analysis and market efficiency? and if so, how?', *Journal of International Financial Markets, Institutions and Money* **28**(C), 131–157.

Markowtiz, H. (1991), *Portfolio Selection, Efficient Diversification of Investments*, Wiley-Blackwell.

Menkhoff, L. (1997), 'Examining the Use of Technical Currency Analysis', *International Journal of Finance & Economics* **2**(4), 307–318.

Menkhoff, L., Sarno, L., Schmeling, M. & Schrimpf, A. (2012), 'Currency momentum strategies', *Journal of Financial Economics* **106**(3), 660–684.

Menkhoff, L. & Schlumberger, M. (1995), 'Persistent profitability of technical analysis on foreign exchange markets?', *Banca Nazionale del Lavoro Quarterly Review* **48**(193), 189–215.

Menkhoff, L. & Taylor, M. (2007), 'The obstinate passion of foreign exchange professionals: Technical analysis', *Journal of Economic Literature* **45**(4), 936–972.

Miller, B., Meakin, L., Look, C., & Lee, J. (2017), 'Central Banks Can't Ignore the Cryptocurrency Boom'. [Bloomberg News, Posted on 30-August-2017].
**URL:** *https://www.bloomberg.com/news/articles/2017-08-30/cryptocurrencies-are-new-barbarians-at-the-gate-of-central-banks*

Møller, M. F. (1993), 'A scaled conjugate gradient algorithm for fast supervised learning', *Neural networks* **6**(4), 525–533.

Nakamoto, S. (2009), 'Bitcoin: A peer-to-peer electronic cash system'.
**URL:** *http://bitcoin.org/bitcoin.pdf*

Neely, C. J. (1997), 'Technical analysis in the foreign exchange market: a layman's guide', *Review* pp. 23–38.

Neely, C. J. & Weller, P. A. (1999), 'Technical trading rules in the European Monetary System', *Journal of International Money and Finance* **18**(3), 429–458.

Neely, C. J. & Weller, P. A. (2003), 'Intraday technical trading in the foreign exchange market', *Journal of International Money and Finance* **22**(2), 223–237.

Neely, C. J., Weller, P. A. & Ulrich, J. M. (2009), 'The Adaptive Markets Hypothesis: Evidence from the Foreign Exchange Market', *Journal of Financial and Quantitative Analysis* **44**(02), 467–488.

Oberlechner, T. (2001), 'Importance of Technical and Fundamental Analysis in the European Foreign Exchange Market', *International Journal of Finance & Economics* **6**(1), 81–93.

Olson, D. (2004), 'Have trading rule profits in the currency markets declined over time?', *Journal of Banking & Finance* **28**(1), 85–105.

Osler, C. L. (2000), 'Support for resistance: technical analysis and intraday exchange rates', *Economic Policy Review* (Jul), 53–68.

Park, C.-H. & Irwin, S. (2007), 'What do we know about the profitability of technical analysis?', *Journal of Economic Surveys* **21**(4), 786–826.

Park, J.-S. (2016), 'Statistical testing of technical trading rule profitability'. Available at: http://hdl.handle.net/1959.14/1116432.

Park, J.-S. et al. (2016), 'Statistical testing of technical trading rule profitability'.

Plassaras, N. A. (2013), 'Regulating digital currencies: bringing bitcoin within the reach of imf', *Chicago Journal of International Law* **14**(1), 377–407.

Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R. & Lightfoot, G. (2015), 'Price fluctuations and the use of bitcoin: An empirical inquiry', *International Journal of Electronic Commerce* **20**(1), 9–49.

Politis, D. N. & Romano, J. P. (1994), 'The stationary bootstrap', *Journal of the American Statistical Association* **89**(428), 1303–1313.

Politis, D. & White, H. (2004), 'Automatic block-length selection for the dependent bootstrap', *Econometric Reviews* **23**(1), 53–70.

Pring, M. (1991), *Technical Analysis Explained: the successful investor's guide to spotting investment trends and turning points.*, McGraw-Hill.

Qi, M. & Wu, Y. (2006), 'Technical trading-rule profitability, data snooping, and reality check: Evidence from the foreign exchange market', *Journal of Money, Credit and Banking* **38**(8), 2135–2158.

Romano, J. P. & Wolf, M. (2005), 'Stepwise multiple testing as formalized data snooping', *Econometrica* **73**(4), 1237–1282.

Saacke, P. (2002), 'Technical analysis and the effectiveness of central bank intervention', *Journal of International Money and Finance* **21**(4), 459–479.

Scholtus, M. & van Dijk, D. (2012), High-Frequency Technical Trading: The Importance of Speed, Tinbergen Institute Discussion Papers 12-018/4, Tinbergen Institute.
**URL:** *https://ideas.repec.org/p/tin/wpaper/20120018.html*

Schulmeister, S. (1987), 'An essay on exchange rate dynamics', *WZB Discussion Paper* .

Schulmeister, S. (2009), 'Profitability of technical stock trading: Has it moved from daily to intraday data?', *Review of Financial Economics* **18**(4), 190–201.

Shynkevich, A. (2016), 'Predictability in bond returns using technical trading rules', *Journal of Banking & Finance* **70**, 55–69.

Sobol, I. & Levitan, Y. L. (1976), 'The production of points uniformly distributed in a multidimensional cube', *Preprint IPM Akad. Nauk SSSR* **40**(3).

Sortino, F. A. & Price, L. N. (1994), 'Performance measurement in a downside risk framework', *the Journal of Investing* **3**(3), 59–64.

Subramanian, H., Ramamoorthy, S., Stone, P. & Kuipers, B. J. (2006), Designing safe, profitable automated stock trading agents using evolutionary algorithms, *in* 'Proceedings of the 8th annual conference on Genetic and evolutionary computation', ACM, pp. 1777–1784.

Sullivan, R., Timmermann, A. & White, H. (1999), 'Data-snooping, technical trading rule performance, and the bootstrap', *Journal of Finance* **54**(5), 1647–1691.

Sullivan, R., Timmermann, A. & White, H. (2001), 'Dangers of data mining: The case of calendar effects in stock returns', *Journal of Econometrics* **105**(1), 249–286.

Sweeney, R. (1986), 'Beating the foreign exchange market', *Journal of Finance* **41**, 163–82.

Sweeney, R. J. (1988), 'Some new filter rule tests: Methods and results', *Journal of Financial and Quantitative Analysis* **23**(3), 285–300.

Taylor, M. & Allen, H. (1992), 'The use of technical analysis in the foreign exchange market', *Journal of International Money and Finance* **11**(3), 304–314.

Tenti, P. (1996), 'Forecasting foreign exchange rates using recurrent neural networks', *Applied Artificial Intelligence* **10**(6), 567–582.

Thaler, R. (1987), 'Seasonal movements in security prices ii: Weekend, holiday, turn of the month, and intraday effects', *Journal of Economic Perspectives* **1**(2), 169–77.

Urquhart, A. (2017), 'Price clustering in bitcoin', *Economics Letters* **159**, 145 – 148.

Wang, F., Philip, L. & Cheung, D. W. (2014), 'Combining technical trading rules using particle swarm optimization', *Expert Systems with applications* **41**(6), 3016–3026.

West, K. (1996), 'Asymptotic inference about predictive ability', *Econometrica* **64**(5), 1067–84.

White, H. (2000), 'A reality check for data snooping', *Econometrica* **68**(5), 1097–1126.

Wilder, J. W. (1978), *New concepts in technical trading systems*, Trend Research.

Wyckoff, R. D. (1910), *Studies in tape reading*, Traders Press.

Yao, J., North, P. & TAN, C. L. (2001), Guidelines for financial forecasting with neural networks, *in* 'Proceedings of International Conference on Neural Information Processing', pp. 14–18.

Zarrabi, N., Snaith, S. & Coakley, J. (2017), 'FX technical trading rules can be profitable sometimes!', *International Review of Financial Analysis* **49**(C), 113–127.