Market Efficiency and Technical Trading Profits in Cryptocurrencies

Michael McGarry

Queen’s University Belfast

School of Management

A dissertation submitted for the degree

Master in Quantitative Finance

September, 2018

Word Count: 14,002

Acknowledgements

I would like to express my sincere thanks to my supervisor Dr Tony Klein for his fantastic help and patience throughout this dissertation, his guidance has been invaluable. Additionally I would also like to thank the staff from the Queen's University Belfast Management School for their teaching throughout the year, especially Dr Alan Hanna for teaching me the technical skills necessary for this research. Finally I would like to thank my family and friends for their words of encouragement over the past few months.

Abstract

This paper examines the performance of technical trading strategies in cryptocurrency markets as a test for the presence of weak form market efficiency. Five different types of strategy are tested; momentum, contrarian, moving average, filter rules and trading range breaks. These strategies are tested on four cryptocurrencies; Bitcoin, Litecoin, Ripple and Ethereum, as well as a cryptocurrency index, the CRIX. We find that cryptocurrency markets are not weak form market efficient by showing that 50 of the 70 strategies earn average annual returns which are large and significant. These results are robust with respect to increased transaction costs, as well as during a period of significant downturn in the market. The top performing strategies are shown to be a 5-20 moving average strategy and a 7.5 per cent filter rule, and further research is suggested into contrarian strategies in cryptocurrency markets as the data becomes available.

Contents

1. INTRODUCTION 1
2. LITERARY REVIEW 4
3. DATA 12
4. METHODOLOGY 14
   4.1 Momentum Strategies 14
   4.2 Contrarian Strategies 16
   4.3 Moving Average Crossover Strategies 18
   4.4 Filter Rules 19
   4.5 Trading Range Break Strategies 21
   4.6 Transaction Costs 22
   4.7 Data Snooping 22
   4.8 Caveat on Short Selling Cryptocurrencies 23
5. RESULTS 25
   5.1 Momentum (Weekly) 25
   5.2 Momentum (Monthly) 25
   5.3 Contrarian (Weekly) 27
   5.4 Contrarian (Monthly) 28
   5.5 Moving Average Crossover 30
   5.6 Filter Rules 31
   5.7 Trading Range Break 33
   5.8 Differences in Returns from Buy and Sell Signals 34
   5.9 Implications for Market Efficiency 36
   5.10 Comparison of Results across Strategies 37
   5.11 Comparison of Results across Assets 38
   5.12 Robustness Checks 39
      5.12.1: Transaction Costs Increased to 1 per cent 39
      5.12.2 Results during the 2018 Downturn 42
6. CONCLUSION 45
7. APPENDIX 48
8. BIBLIOGRAPHY 75

1. INTRODUCTION

Within the efficient markets hypothesis, Fama (1970) states that there are three different levels to market efficiency; weak form, semi-strong form and strong form. Weak form market efficiency alleges that current market prices are fully reflective of all of the information contained in their historical prices, which suggests that there are no abnormal profits to be made from trading based solely on historical prices and trends (technical analysis). Semi-strong form market efficiency suggests that current prices are fully reflective of all publicly available information, for example company earnings or dividends announcements, so that there are no abnormal profits to be made from trading based on this information (fundamental analysis). Strong-form efficiency states that current prices are reflective of all public and private information about an asset so there are no abnormal profits to be made from actively trading in the market.

There has been a great deal of research devoted to testing weak-form market efficiency which can be generally summarised as providing mixed results (Park and Irwin, 2017). While this research focuses on traditional financial markets such as equities, currencies and commodity futures, ranging from the late 1800s right up to the present, there is a relatively new market which has yet to be extensively tested for market efficiency – that is the market for cryptocurrencies.

Bitcoin was created by Nakamoto (2008) and its creation, adoption and growth inspired many other cryptocurrencies (altcoins) to be created in the following years. Currently, CoinMarketCap (2018a) lists 1,910 cryptocurrencies in circulation and the number is always increasing – with over 600 new initial coin offerings (ICOs) taking place in the first six months of 2018 (Coinschedule, 2018). For a more detailed description of Bitcoin and how it works, see Böhme, Christin and Edelman (2015) and Narayanan et al (2016). For a detailed description of the markets for Bitcoin and altcoins see White (2015).

Alongside the rapid growth in the quantity of cryptocurrencies available for trading, recently there has also been huge growth in the market capitalisation of cryptocurrencies which has driven more research into the market. CoinMarketCap (2018b) is generally assumed to be the best database of cryptocurrency price history, and it shows a growth in total market capitalisation of all cryptocurrencies from around $1.35 billion in May 2013 to $414.45 billion in May 2018, with a peak of around $795.8 billion in January 2018.

The enormous growth of cryptocurrency markets leads to two questions; firstly, are cryptocurrency markets efficient? Secondly, can an investor make money by actively trading in the market?

This research seeks to answer both of these questions and add to the small body of literature surrounding market efficiency and technical analysis in cryptocurrency markets. Several popular technical trading strategies are identified through financial literature and tested on four cryptocurrencies; Bitcoin (BTC), Litecoin (LTC), Ripple (XRP) and Ethereum (ETH), as well as a cryptocurrency market index (CRIX). If it is possible for the strategies identified to consistently generate excess returns, then these markets will not satisfy Fama's (1970) definition of weak form market efficiency.

The five broad strategy types which are tested are momentum strategies, contrarian strategies, moving average crossovers, filter rules, and trading range breaks. Each of the five strategy types has a variation of individual strategies, giving a total of 70 different individual strategies which are tested on the data.

We show that 50 of the 70 strategies tested produce average annual returns which are positive and statistically significant. Due to data constraints in the cryptocurrency market, contrarian strategies are not calculated using long enough time periods to experience the price reversals noted in the literature (Jegadeesh and Titman 1993). This explains the negative performance of nearly all of these strategies. Excluding contrarian strategies, 48 of 52 strategies tested produce statistically significant positive annual returns. The large proportion of technical trading strategies which produce excess returns allows us to reject the notion of weak form market efficiency in cryptocurrency markets.

To test the robustness of the strategies two checks are performed; firstly the transaction cost per trade is increased in an attempt to account for other costs such as the market impact of trading, and secondly the returns during the 2018 downturn period in the cryptocurrency market are studied to observe if the strategies are still profitable during a downturn. Excluding contrarian strategies, 50 per cent of strategies tested produce positive returns both with increased transaction costs and during the 2018 downturn period, demonstrating the robustness of the results.

By comparing both the returns of the strategies tested as well as the results from common risk measures, we select the 5-20 moving average strategy and the 7.5 per cent filter rule as the top performing technical trading strategies an investor can use to generate excess returns in cryptocurrency markets.

The rest of this paper is laid out as follows: section 2 describes the key literature in this area of research, section 3 provides a summary of the data, section 4 describes the trading strategy methodology employed, section 5 provides the results and their analysis and implications, section 6 concludes, section 7 contains an appendix and section 8 is a bibliography.

2. LITERARY REVIEW

Early studies on weak form market efficiency find that technical trading rules are not profitable. Fama and Blume (1966) investigate the use of filter rules on the 30 individual stocks of the Dow Jones Industrial Average from 1956 to 1962. They find that before accounting for transaction costs, filter rules were outperformed by the buy and hold strategy for all but two of the securities.

These findings are supported by the research of Jensen and Bennington (1970) who find that technical trading rules do not earn significantly more than the buy and hold strategy, and that once adjusted for risk these strategies underperform the buy and hold benchmark for securities data from 1926 to 1966.

Similar support for weak form market efficiency is found by Van Horne and Parker (1967) and by James (1968). Both of these studies focus on various trading rules based on a moving average of stock prices, and find that none of these rules beat the buy and hold strategy.

Despite the academic approval of weak form market efficiency and the theory that stock prices follow a random walk (Malkiel and McCue, 1985), Menkhoff and Schmidt (2005) find in their survey of German pension and mutual fund managers that most managers do use some form of technical analysis in making their investment decisions. They note that managers mostly rely on the buy and hold strategy, but also use momentum and contrarian strategies in a complimentary fashion. Interestingly, they show that the preference of a manager to adopt either a momentum or a contrarian strategy depends on their behavioural tendencies; momentum traders are the least risk averse, whilst contrarian traders are comparatively overconfident in their approach.

Menkhoff (2010) builds upon the original survey by expanding it to 692 fund managers across five countries and states that ‘the vast majority rely on technical analysis’. He finds that 87% of fund managers ‘put at least some importance on technical analysis’, and that it is ‘the most important form of analysis for decisions with forecasting horizons of some weeks’.

These surveys conducted by Menkhoff and Schmidt (2005) and Menkhoff (2010) focus on momentum and contrarian technical trading strategies. Jegadeesh and Titman (1993) study the profitability of a momentum strategy which buys past 'winners' and sells past 'losers' based on their previous 6-month returns and holds them for 6-months forward, and they note that this strategy 'realizes a compound excess return of 12.01% per year on average'. Jegadeesh and Titman (2001) revisit these results and show that they continue into the 1990's. They find that behavioural models explain the profitability of momentum strategies well; investors initially underreact to market news and the delayed overreaction to information will 'push the prices of winners (losers) above (below) their long-term values'. Significant return reversals are noted to occur 4 to 5 years after the formation date of the momentum strategy.

These momentum strategies are cross sectional in nature, that is to say that they rank a group of assets by their performance in a given period and will purchase the relative best performers (winners) and short sell the relative worst performers (losers). Moskowitz et al (2012) created a new approach to momentum trading referred to as 'time series momentum' (TSMOM). Rather than buying the relative winners and selling the relative losers in a cross section of assets, TSMOM instructs an investor to buy any asset that has a positive return over the lookback period, and similarly will short any asset with a negative return over the same lookback period.

Moskowitz et al (2019) find that TSMOM strategies deliver 'substantial abnormal returns' when applied to equity indices, currencies and commodity and bond futures and that the best performance from these strategies occurs during periods of extreme market volatility. They note that TSMOM returns persist up to a period of 12 months and that prices partially reverse over longer periods.

Whilst a momentum strategy consists of buying stocks that are doing well and selling those that are performing poorly, a contrarian strategy is the opposite. A contrarian strategy seeks to capitalise from a price reversal; buying stocks which have performed poorly and selling stocks which have performed extremely well in the expectation that their performance will reverse. This strategy is based on the work of DeBondt and Thaler (1985) who find that investors overreact to news, meaning that they will drive the price too far above its fundamental value after good news, or drive the price too far below its fundamental value upon bad news. This overreaction means a contrarian strategy can be profitable when the stocks experience a reversal toward their fundamental value. This is a long term strategy as they find that losers will outperform winners after around 3-5 years.

Contrarian investment strategies are supported by the research of Lakonishok et al (1994) who find that buying out-of-favour stocks has outperformed buying 'glamour' stocks from 1968 to 1990. They contribute to the literature on contrarian strategies by suggesting that buying out-of-favour stocks appears to be no riskier than buying 'winners' i.e. stocks that have performed well. Since the returns are higher and do not contain more risk, abnormal profits can be achieved using a contrarian strategy.

Behavioural models can explain the profitability of this technical trading strategy; Jegadeesh and Titman (1995) find that most of the profits of contrarian strategies can be attributed to investors' initial overreaction followed by a price reversal toward the fundamental value.

Momentum (price continuation) and contrarian (price reversal) trading strategies may initially seem like contrasting strategies but this is not necessarily the case. Conrad and Kaul (1998) explain how these strategies can be used simultaneously due to the time periods in which they are usually observed to be profitable. Momentum strategies are said to be profitable in the medium term (3-12 months) and contrarian strategies are profitable in the long term (3-5 years).

In the same study, Conrad and Kaul (1998) investigate the profitability of the two strategies and found that of the 120 strategies they tested; 'less than 50% of these yielded statistically significant profits and both strategies were equally likely to be successful'.

Since the earlier studies into momentum and contrarian strategies from Jegadeesh and Titman (1993) and DeBondt and Thaler (1985) respectively, there has been considerable attention drawn to testing these strategies in a wide range of financial markets across many different assets.

Within Europe, Forner and Marhuenda (2003) show that these strategies are profitable in the Spanish stock market, Schiereck et al (1999) show profitability in Germany, Mengoli (2004) finds them to be profitable in the Italian equity market and Rouwenhorst (1998) observes profitability in momentum strategies across twelve separate European markets.

Outside of the developed markets of the US and Europe, Muga and Santamaria (2007) find momentum profits can be achieved in four emerging markets in Latin America (Argentina, Brazil, Chile and Mexico). In addition to this, Hameed and Kusnadi (2002) find evidence of momentum profits across six Asian countries at the individual country level, and Hurn and Pavlov (2003) find positive momentum returns in Australian stocks.

Aside from equity markets, Okunev and White (2003) show that momentum profits can be achieved in foreign currency markets, whilst Menkhoff and Taylor (2007) go into great detail about the extensive use of technical analysis in foreign exchange markets. In addition to this, Miffre and Rallis (2007) and Shen et al (2007) observe momentum profits in commodity futures.

It is clear then that momentum and contrarian technical trading strategies can be used profitably, but these are not the only forms of technical analysis available to the investor. Brock, Lakonishok and LeBaron (1992) describe the use of 'two of the simplest and most popular technical rules: moving-average oscillator and trading range break (resistance and support levels)'. They apply these rules to the Dow Jones Industrial Average index from 1897 to 1986 and find that the rules 'have a strong predictive power' and that they generate excess returns. They also note that for moving-average rules, buy signals generate higher returns with less volatility than sell signals.

This framework is repeated in a similar study by Hudson, Dempsey and Keasey (1995) who apply the same techniques to a UK dataset and again find that technical trading rules have a predictive ability. However, they claim that 'in the presence of actual trading costs, the returns are unlikely to make returns over a buy and hold strategy'.

Analogous to momentum strategies, the simple technical trading strategies described by Brock, Lakonishok and LeBaron (1992) can also be applied to markets other than stocks. Levich and Thomas (1991) study simple trading rules in foreign exchange markets from 1976 to 1990 and find the profitability of these strategies to be highly significant. They do note however that these trading profits decline in each sub-section of their data which could be an indicator that competition for these trading profits is driving the market to become more efficient over time.

In commodity futures markets, Szakmary, Shen and Sharma (2010) observe some simple trading rules (moving average and channel strategies) over a 48 year period across 28 commodity futures markets and find that these strategies 'yield positive mean excess returns net of transactions costs in at least 22 of the 28 markets'.

An accurate summary of the literature on technical trading rules is provided by Lento and Gradojevic (2007) who state 'findings are not significant and robust enough to allow for a generalisation that all technical trading rules are profitable for all securities'. However, they go on to add, 'Results do suggest that technical trading rules can provide some relevant investment information and be used for making investment decisions.' In their own study of these trading rules, they find that moving average and trading range break rules generate excess returns, and that in some cases filter rules may be useful.

Research into the market efficiency of cryptocurrencies has grown over the last few years. In one of the earliest studies, Urquhart (2016) studies Bitcoin prices from 2010 to 2016 and finds that Bitcoin prices are not weak-form efficient as described by Fama (1970). He notes that whilst the price of Bitcoin is inefficient over the full time period, it may be becoming less inefficient over time.

This suggests that competition could be driving the market towards greater efficiency as the volume of Bitcoin trading increased greatly over the study period.

Subsequent studies have attempted to build on the initial work of Urquhart (2016). Nadarajah and Chu (2017) adapt the original data of Bitcoin returns by raising the returns to the power of 17. They argue that this leads to no information being lost and that when these adjusted returns are tested they show that the market is indeed weak-form efficient. This is in contrast to a study in the same year by Bariviera (2017) who found that Bitcoin returns are persistent (i.e. the market is not weak-form efficient) from 2010 to 2014, but from 2014 onwards the returns seem to be compatible with white noise. These findings agree with the original study by Urquhart (2016) that the Bitcoin market was not weak form efficient but is improving in its efficiency over time.

Further follow up research into this topic has since gained mixed results. Jiang, Nie and Ruan (2017) find that the Bitcoin market has a high degree of inefficiency – noted by the relatively high Hurst ratio they observe. They also state that 'the Bitcoin market does not become more efficient over time' which is a contrast to Urquhart (2016) and Bariviera (2017). Kristoufek (2018) supplements this by finding 'strong evidence of Bitcoin markets remaining mostly inefficient between 2010 and 2017'. He adds to this by saying that the only time markets are judged to be performing efficiently is in the cooling-down periods after a bubble like price surge. Despite these studies stating that the Bitcoin market is inefficient, Tiwari et al (2018) conclude the opposite and state that Bitcoin returns are informationally efficient apart from two short time periods in their study.

In a more expansive paper that looks at Bitcoin as well as three other cryptocurrencies (Litecoin, Ripple and Dash), Caporale, Gil-Alana and Plastun (2018) find that all four cryptocurrencies exhibit persistence in their prices which represents evidence of market inefficiency across different cryptocurrencies. They note that the degree of price persistence changes over time; with Litecoin becoming significantly more efficient over time. The other three cryptocurrencies however seem to oscillate around a mean value of price persistence. This study goes on to suggest that trend trading strategies can generate abnormal profits in the cryptocurrency market, which is an area of research that this paper explores.

There is very little literature in the area of testing technical trading strategies which was suggested by Caporale, Gil-Alana and Plastun (2018), indeed one of the few papers that studies this area is by two of the same authors (Caporale and Plastun, 2018). They test momentum and contrarian trading strategies across the same four cryptocurrencies that they tested in their original paper. They find that contrarian strategies are not profitable and that momentum strategies have predictive ability but may not be profitable due to transaction costs possibly eradicating profits. They do not test any of the other popular trading strategies from financial literature such as moving average, trading range breaks or filter rules. An issue with this paper is that the contrarian strategies they test are focused on daily 'overreactions' of the price whilst the literature suggests contrarian strategies should be implemented in the long term. Therefore, the contrarian strategies tested in this research focus on daily returns across periods of weeks and months, rather than days.

In a similar study, Kosc, Sakowski and Slepaczuk (2018) use a dataset of 1200 cryptocurrencies between 2014 and 2017 to assess the profitability of momentum and contrarian strategies on weekly price data. They do not use short selling in either of their strategies, and find a strong daily contrarian effect and a lack of a momentum effect. Just like Caporale and Plastun (2018), this study focuses on the same time periods for both momentum and contrarian strategies – which again contradicts the literature in traditional financial markets which suggests contrarian strategies should be used over a longer timeframe.

Another issue with this paper is that they test these strategies on the top 100 cryptocurrencies each week by market capitalisation. While this may seem like a sound implementation, I believe this includes too many 'small' coins in terms of market capitalisation. These coins often lack the depth of liquidity associated with the more popular coins, and this lack of liquidity means that relatively large orders can have a substantial price impact. The authors actually note that there is a limitation with implementing some of their strategies if there is a lack of liquidity in certain coins because of this price impact, so this research will focus on four of the top cryptocurrencies by market capitalisation to avoid this issue.

The simple trading rules described by Brock, Lakonishok and LeBaron (1992) are extensively studied in traditional financial markets, but the opposite is the case in cryptocurrency markets. There is however one study that focuses exclusively on moving average trading rules (Detzel et al, 2018). In this research, the authors conclude that Bitcoin, Ethereum and Ripple returns are all predictable using 5-100 day moving averages of their prices both in and out of sample. Whilst this is a compelling result, the authors fail to properly incorporate the influence of typical transaction costs on their strategies and instead make note of the maximum transaction cost which would eliminate the alpha of their moving average strategy.

This research builds on the work of Detzel et al (2018) by testing moving average strategies on several cryptocurrencies, utilising a typical transaction cost found in the market. Section 4.6 describes the structure of typical transaction costs in cryptocurrency markets, and outlines the transaction costs applied to the strategies tested in this paper.

A tabular summary of the key literature in market efficiency and technical trading strategies for both traditional financial markets and cryptocurrencies is provided in Table 1.

3. DATA

The dataset used for this research includes the daily closing prices of four cryptocurrencies and one cryptocurrency index. The cryptocurrencies are Bitcoin (BTC), Litecoin (LTC), Ripple (XRP) and Ethereum (ETH). Bitcoin was selected because it was the first cryptocurrency to gain mainstream adoption and has consistently held the largest market capitalisation of any cryptocurrency since it was created. The other cryptocurrencies were selected to provide exposure to different cryptocurrency technologies and because of their relatively large market capitalisations. As of June 2018, these four cryptocurrencies make up over 64 per cent of the total cryptocurrency market capitalisation, with Bitcoin making up 38 per cent of the cryptocurrency market alone.

The cryptocurrency index used is the CRIX. This is an index consisting of twenty cryptocurrencies that are selected using the 'dynamic AIC based methodology' as this 'results in indices with stable properties.' (Härdle and Trimborn, 2015). CRIX provides a benchmark for the cryptocurrency market, just as the S&P500 or the DAX30 provide benchmarks for the financial industry. For information on the design of CRIX, see Härdle and Trimborn (2015). Whilst trading in the CRIX is not actually available to any investors, using it to test these strategies provides us with a proxy for the cryptocurrency market in general.

Historical prices for all assets were taken from 1 June 2013, or the earliest possible price if the asset only started trading after this date. The data then runs as far as 1 June 2018 for all assets.

Data for the four cryptocurrencies is provided by CoinMarketCap (2018a) as it is regarded as a reliable source of cryptocurrency market information. Since cryptocurrency markets are considered to be continuously traded, they are open 24 hours a day, every day of the year. Therefore, the markets themselves have no opening time or closing time, and as such have no actual opening price or closing price. For this reason, the 'closing price' used for each observation is the closing price reported on CoinMarketCap, which calculates the closing price to be the last price available on that date in the UTC time zone (Coordinated Universal Time).

Summary statistics for the daily returns data of each asset is provided in Table 2. This table shows that every asset studied experiences a positive mean daily return, meaning they are all upward sloping. They are all also characterised by having excess kurtosis, meaning that there is a higher probability of extremely large positive or negative daily returns than an asset which has its returns characterised by the normal distribution. This in essence indicates that cryptocurrency markets can be extremely volatile, such that extremely large price increases and decreases are not uncommon.

4. METHODOLOGY

4.1 Momentum Strategies

The momentum strategies used in this paper are based on the work of Moskowitz et al (2012). These are time-series momentum strategies in that the decision to go either long or short an asset is based solely on the previous returns of that asset and not the relative returns of the asset compared to a number of other assets. These momentum strategies are calculated based on either weekly or monthly lookback and holding periods.

If the lookback period returns are positive, then the time series momentum strategy will buy the asset and hold it for the length of the holding period.

If the lookback period returns are negative, then the time series momentum strategy will short the asset and hold it for the length of the holding period.

The log return, r, for a given strategy at time t, with a certain lookback period of length L, holding period of length H, and price P, is calculated as either:

$$\boldsymbol{r_t | \log\left(\frac{P_t}{P_{t-L}}\right) > 0 = \log\left(\frac{P_{t+H}}{P_t}\right)}$$

Or

$$\boldsymbol{r_t | \log\left(\frac{P_t}{P_{t-L}}\right) < 0 = -1 \times \log\left(\frac{P_{t+H}}{P_t}\right)}$$

The returns for momentum strategies are calculated at the start of each period for every combination of lookback and holding periods. The weekly strategies are calculated on the first day of each week, and the monthly strategies are calculated on the first day of each month.

The result of this is that each individual momentum strategy generates a list of signals and momentum returns for each cryptocurrency asset studied. These lists combine to produce a full set of signals and returns for each individual momentum strategy across all cryptocurrency assets, from which the strategies performances are analysed.

The lookback and holding periods used for weekly strategies are 2-weeks, 4-weeks and 8-weeks. Momentum returns are calculated for every combination of lookback and holding periods, resulting in nine weekly momentum strategies.

The lookback and holding periods used for monthly strategies are 3-months, 6-months, 9-months and 12-months. Momentum returns are calculated for every combination of lookback and holding periods, resulting in sixteen monthly momentum strategies.

The timeframes for these momentum strategies were chosen because they can be considered 'short to medium term' as the findings in the literature suggest this is when momentum strategies are profitable. Specifically, Moskowitz et al (2012) note that the assets in their study exhibit 'strong return continuation for the first year, and weaker reversals in the next four years.' This agrees with the finding of Jegadeesh and Titman (1993) who find that a momentum portfolio formed based on a 6-month lookback period will achieve abnormal returns in the first 12 months, however it will lose more than half of this return over the following 24 months. This is why a maximum holding period of 12 months is selected for our momentum strategies.

Annualised returns are reported for momentum strategies by dividing individual strategy returns by the length of their holding period and multiplying by 12 for monthly strategies or 52 for weekly strategies.

In total, there are 3040 monthly momentum returns and 9606 weekly momentum returns calculated.

4.2 Contrarian Strategies

The contrarian strategies used in this paper are similar to the momentum strategies in that they are time-series in nature and based on the work of Moskowitz et al (2012).

Contrarian returns are calculated in the same fashion as momentum returns, however instead of purchasing the asset if lookback returns are positive, a contrarian strategy will short the asset if lookback returns are positive.

Likewise, a contrarian strategy will buy the asset if the lookback returns are negative as opposed to a momentum strategy, which will do the opposite.

The log return, r, for a given strategy at time t, with a certain lookback period of length L, holding period of length H, and price P, is calculated as either:

$$\boldsymbol{r_t | \log\left(\frac{P_t}{P_{t-L}}\right) > 0 = -1 \times \log\left(\frac{P_{t+H}}{P_t}\right)}$$

Or

$$\boldsymbol{r_t | \log\left(\frac{P_t}{P_{t-L}}\right) < 0 = \log\left(\frac{P_{t+H}}{P_t}\right)}$$

Analogous to momentum strategies, the returns for weekly contrarian strategies are calculated on the first day or each week and the returns to monthly contrarian strategies are calculated on the first day of each month.

The lookback and holding periods used for the weekly strategies are 8-weeks, 12-weeks and 16-weeks. Contrarian returns are calculated for every combination of lookback and holding periods, giving a total of nine different weekly contrarian strategies.

The monthly strategies use lookback and holding periods that are 9-months, 12-months and 18-months long. Contrarian returns are calculated for every combination of lookback and holding periods, giving nine different monthly contrarian strategies.

The timeframes for these contrarian strategies are longer than those for the momentum strategies, and were chosen in an attempt to replicate those used by DeBondt and Thaler (1985) as the evidence suggests that contrarian strategies only provide positive returns over long periods.

Contrarian returns are annualised in the same fashion as momentum returns; individual strategy returns are divided by the length of the holding period and multiplied by 12 for monthly strategies, and by 52 for weekly strategies.

One issue with the contrarian strategies used in this paper is that the lookback and holding periods are not long enough. The literature suggests that momentum and contrarian strategies are profitable due to investors' initial under-reaction in the short to medium term, which is eventually corrected by an over-reaction in the long term. Jegadeesh and Titman (2001) note that these price reversals occur 4 to 5 years after the formation date of the strategy. Unfortunately, the market for cryptocurrencies is so young that there is simply not enough data to create a strategy with a four to five year lookback, and a four to five year holding period. The result of this is that the maximum lookback and holding periods used in this study are eighteen months long.

A concern with the technique employed to generate the returns for momentum and contrarian strategies is that these strategies will often contain overlapping data, yet for the basis of this research, we use the overlapping data and treat it as a group of separate strategies. An example of this is a momentum strategy with a 6-month holding period. For any given month, the returns from this strategy contain the information from the returns over the next six months. The returns for the same strategy formed one month after the original will therefore contain five months of the same returns, plus one new month of returns on the end.

This approach to testing the performance of momentum and contrarian strategies may not be ideal, but it is necessary considering the limitations of the length of the time series data used. The advantage of this approach is that it provides more results for the strategies tested. The dataset available for cryptocurrency prices is relatively short compared to datasets used in the literature on traditional financial markets, many of which span several decades. Making use of this overlapping data is therefore necessary to infer any results from our strategies.

4.3 Moving Average Crossover Strategies

A moving average (MA) crossover strategy works by tracking two different length simple moving averages of the time series; one shorter length MA (SMA) and one longer length MA (LMA).

The MA strategies used in this research are 'Variable Length Moving Averages' (VMAs). The rules for entering a trade in this strategy are simple; if the value of the SMA 'crosses over' from being less than the LMA to being greater than the LMA, a trend is thought to be initiated and so a 'buy-signal' is created and a long position is opened. This position is held until the SMA 'crosses over' once again – this time from being greater than the LMA to being less than the LMA. Once this happens it is considered a 'sell-signal' whereby not only is the position liquidated, but a short position in the asset is undertaken.

The first trade in the VMA strategy is opened after the SMA 'crosses over' the LMA for the first time in the time series, regardless if it crosses from below or above.

Once the first position is opened in this VMA strategy, the strategy is constantly 'in' the market. This is because any time a signal is generated to close out a position, that same signal is used to open a position in the opposite direction than the previous signal.

Each MA strategy produces a list of buy and sell signals and their respective prices. From these signals, s, and prices, P, we calculate the log returns, r, as below.

For a buy signal:

$$\boldsymbol{r_s = \log\left(\frac{P_{s+1}}{P_s}\right)}$$

For a sell signal:

$$\boldsymbol{r_s} = -\mathbf{1} \times \mathbf{log}\left(\frac{\boldsymbol{P_{s+1}}}{\boldsymbol{P_s}}\right)$$

Where 's+1' refers to the next signal generated in the time series.

Some of the MA strategies employed use a 'band'. The band is a percentage level that the SMA must exceed the LMA by when they 'cross over' before a position is opened. For example, a one per cent band would mean that the SMA would have to move from a value less than the LMA to a value greater than the LMA multiplied by 1.01 before a long position is opened. For a short position to be opened, the SMA must cross over and be less than the LMA multiplied by 0.99.

The moving average strategies used in this paper replicate those used by Levich and Thomas (1991) and by Brock, Lakonishok and LeBaron (1992). Table 3.3 provides a list of the strategies used and their bands.

Moving average strategy returns are annualised by dividing the total returns of each moving average strategy at the asset level by the length of the time series for that asset in years. This gives the total return per year for that strategy for each asset. Total average returns are calculated as a weighted average of the annual individual asset returns, where the length of each time series is the weight used.

4.4 Filter Rules

Filter rules are trading rules that seek to exploit short term momentum in prices to generate profits.

The 'filter' on a filter rule refers to a percentage value of price change used to generate buy and sell signals. For an 'x' per cent filter, a buy signal is generated when the price of the asset rises above its most recent trough by more than x. Similarly, a sell signal is generated when the price of the asset falls below its most recent peak by more than x.

Each filter rule is applied to the time series of cryptocurrency prices which provides a complete list of buy and sell signals and their respective prices. From these signals, s, and prices, P, the log returns, r, of each rule are calculated as below.

For a buy signal:

$$\boldsymbol{r_s = \log\left(\frac{P_{s+1}}{P_s}\right)}$$

For a sell signal:

$$\boldsymbol{r_s = -1 \times \log\left(\frac{P_{s+1}}{P_s}\right)}$$

Where 's+1' refers to the next signal which is generated in the time series.

Filter rules are similar to MA rules in that once the first position is opened in the time series, the rule is constantly 'in' the market until the end of the time series. This is because once the initial position is established, that position is held until a signal is generated to reverse the trade whereby the position is then liquidated and an opposite position is undertaken.

Ten different Filter Rules are applied to the dataset; these are 0.5, 1, 2, 3, 4, 5, 7.5, 10, 15 and 20 per cent filters. The first six replicate those used in Levich and Thomas (1991). Four larger filters have been selected that are in a similar range to Dooley and Schafer (1984). These four largest filters used have been added to observe their performance in cryptocurrency markets, as these are considered more volatile than the traditional markets that the literature has tested filter rules on previously.

Annual returns for filter rules are calculated by dividing the total returns of each filter rule strategy at the asset level by the length of that asset's respective time series in years. This gives the average return per year for that strategy for each asset. Total average returns across all assets are calculated as a weighted average of annual individual asset returns, where the length of each time series is the weight used.

4.5 Trading Range Break Strategies

A Trading Range Break (TRB) strategy is one that uses the minimum and maximum values (i.e. the trading range) of a time series over a certain lookback period to generate a buy or a sell signal. The strategy generates a buy signal when the current price of the asset rises above the maximum asset value over the previous ‘n’ trading days. Similarly, the strategy generates a sell signal when the current price of the asset falls below the minimum asset value over the previous ‘n’ trading days.

Once a buy or a sell signal is generated, a long or a short position in the asset is opened and held for a fixed period of ten days before being closed and realising any gains or losses.

Using these signals, log returns, r, are calculated at time, t, using the price, P as below.

If the signal is a buy signal:

$$\boldsymbol{r_t = \log\left(\frac{P_{t+10}}{P_t}\right)}$$

If the signal is a sell signal:

$$\boldsymbol{r_t = -1 \times \log\left(\frac{P_{t+10}}{P_t}\right)}$$

There is the possibility with this strategy to have more than one position open at a given time, depending on how the time series has moved. For example, a rise above the maximum from the last 150 trading days could trigger a long position to be opened, and another 4 days later the 150-day maximum could be surpassed again, meaning two long positions are held concurrently.

Just like the MA strategies, TRBs can make use of ‘bands’, meaning positions are only opened when prices move past the maximum or minimum by more than a certain percentage.

The six TRB strategies used in this research are the same ones used by Brock, Lakonishok and LeBaron (1992), they are the 50-day, 150-day and 200-day ranges, each with and without a 1 per cent band.

Trading range break returns are annualised by calculating the average number of trades generated by each strategy per year. The average return per trade is calculated by summing total returns and dividing the answer by total number of trades, this is multiplied by the average number of trades per year to result in the average return per year.

4.6 Transaction Costs

Just as an investor in traditional financial instruments will encounter certain transaction costs, so too does the cryptocurrency investor. As of June 2018, CoinMarketCap (2018a) lists over 200 different cryptocurrency exchanges, and each individual exchange has a different structure to their costs for market participation.

An analysis of several of the most popular cryptocurrency exchanges (in terms of 30-day trading volume) shows that transaction costs commonly range from a 0.1 per cent commission to a 0.3 per cent commission per trade depending on the exchange. For this reason, this research conservatively assumes transaction costs to be a set 0.25 per cent fee for each individual trade.

Some exchanges also apply fees for depositing funds in order to buy cryptocurrency, but for the basis of this research, these fees are not considered. Instead, as an additional robustness check, we apply a transaction cost of 1 per cent to each trade and compare these results with those from a 0.25 per cent cost in section 5.12.1 of the results.

4.7 Data Snooping

Data snooping is an important area to address in any time series financial research, based around the idea that when testing a large number of trading strategies, some will return profitable results purely out of chance. Sullivan, Timmerman and White (1999) suggest that this is especially a problem when using the same dataset to test several different trading strategies. They state that ‘when such data reuse occurs, there is always the possibility that any satisfactory results obtained may simply be due to chance rather than to any merit inherent in the method yielding the results.’

There is the chance that any research into technical trading strategies will elect only to test and present results for those strategies which are already known to produce favourable results in the dataset used. In order to prevent any suggestions of this type data snooping in this research, all of the variations of trading strategies selected for testing have been previously used in important pieces of research in this area. This limits the potential to test large numbers of variations of each strategy in the hope that some are profitable.

4.8 Caveat on Short Selling Cryptocurrencies

Despite the technical trading strategies explored in this paper all making use of short selling cryptocurrencies as part of their design, the ability to actually short sell cryptocurrencies is not widely available.

The ability to ‘bet against’ future price rises in cryptocurrencies was only introduced in December 2017, when the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME) opened up futures markets for Bitcoin.

Some exchanges have since opened up the ability for investors to trade on margin and short cryptocurrencies, but even with this ability the margins are often much smaller than they are in traditional markets, mostly they are less than 5 times leveraged – with the exception of BitMEX which offers up to 100 times leverage on Bitcoin.

Since the ability to short or bet against cryptocurrencies is a relatively new feature of the markets, most of the short selling performed by the strategies in this paper is only hypothetical in nature as it would not have been possible at the time. Nevertheless, the strategies tested in this research still employ the use of short selling as the ability to do so will only increase in cryptocurrency markets in the future and therefore it is of interest to potential investors.

5. RESULTS

5.1 Momentum (Weekly)

Table 4 provides a breakdown of the average annualised log returns for all the short term weekly momentum strategies. The columns in Table 4 list the assets, lookback and holding periods, number of signals created, and the average annualised returns. The first panel in this table contains the aggregated results for the weekly strategies across all assets, and the following five panels provide the results at the individual asset level.

Results in the first panel show that weekly momentum strategies all result in returns which are large, positive and statistically significant at the 1 per cent level. The results for individual assets are similar, with every strategy resulting in positive returns and 85 per cent of the strategies are statistically significant at conventional levels ($P \leq 0.10$).

The results in the first panel suggest that shorter holding periods produce higher returns since the 2-week holding periods have the highest, the 4-week holding periods the second highest, and the 8-week holding periods the lowest returns across all three lookback periods. Investigating this relationship at the asset level, the same ranking of returns is given by two thirds of strategies, whilst the 2-week holding period produces the highest return in 80 per cent of cases.

The top performing weekly momentum strategy is the 2-week / 2-week strategy, which returns an average of 149 per cent annually. This strategy also results in the highest returns in four out of the five individual assets studied.

5.2 Momentum (Monthly)

Table 5 summarises the results of the medium term monthly momentum strategies. The columns in Table 5 contain the assets, lookback and holding periods, the number signals created, followed by the average annualised returns. Again, the first panel provides a breakdown of the aggregated results across all strategies and the following five panels give results for the individual assets.

For the aggregated results across all assets, every total monthly momentum strategy provides returns which are positive. All but one of the monthly strategies produces returns which are statistically significant, and half of these returns are significant at the 1 per cent level.

Total returns from the monthly momentum strategies vary when we inspect them at the individual asset level. For BTC, returns are all positive and mostly significant with the largest and most significant returns coming at shorter lookback periods. ETH returns meanwhile are also all positive, but significance is limited to those strategies with longer lookback periods, which may be in part due to the lack of sell signals generated for longer lookback periods for ETH.

Returns for LTC and XRP are completely different; 88 per cent of their returns are not statistically significant, which shows that the performance of monthly momentum strategies varies across different cryptocurrency assets and is by no means guaranteed to produce positive returns.

Returns for CRIX mirror the aggregated results in the first panel, this is to be expected since CRIX is an index of 20 of the top cryptocurrencies and the aggregated results essentially represent positions in an index of four of the largest cryptocurrencies, plus CRIX itself.

The best performance comes from the 12-month / 6-month strategy which produces an average annualised continuous return of 105 per cent and is statistically significant at the 1 per cent level. This strategy provides the top performance in three out of the five individual assets, and also results in large statistically significant returns in the other two assets. This is in contrast to the two main momentum papers studies in the literature. Moskowitz et al (2012) find the best returns from a 12-month / 1-month strategy, whilst Jegadeesh and Titman (1993) find a 6-month / 6-month strategy performs best. This paper follows the strategy structure laid out by Jegadeesh and Titman (1993) and so does not generate results of any momentum strategies with holding periods of one month. Our results do show however in five out of the six panels in Table 5 that the 12-month / 6-month strategy outperforms the 6-month / 6-month strategy in cryptocurrency markets.

The profitability of the momentum strategies which have been tested disagrees with the research from Kosk, Sakowski and Slepaczuk (2018) who find a lack of momentum profits in cryptocurrency markets, as 96 per cent of the momentum strategies tested in this research provide statistically significant positive returns.

Caporale and Plastun (2018) test momentum strategies across four cryptocurrencies and find that they have a predictive ability but may not be profitable due to transaction costs. The results from this research agree that momentum strategies have predictive ability, but also go further to say that momentum strategies are profitable in cryptocurrency markets when they are tested using a standard size of transaction cost per trade.

5.3 Contrarian (Weekly)

Table 6 contains the results from the weekly contrarian strategies and as with previous tables, The columns contain the name of the asset, the lookback and holding periods, the number of signals, and the annualised returns. The first panel summarises the aggregate results across all five cryptocurrency assets, and the results for individual assets are contained in the following five panels.

The lookback and holding periods for contrarian strategies used are selected to be longer time periods than those used by the weekly momentum strategies, the reason for this is that contrarian strategies focus on longer term price reversals as opposed to momentum strategies which focus on short term price continuation (Jegadeesh and Titman, 2001).

The first panel shows the aggregated results for weekly contrarian strategies across all assets, and these strategies produce returns which are all negative and statistically significant at the 1 per cent level.

We can immediately draw similarities between the results of the weekly contrarian strategies and the monthly momentum strategies in that they seem to be almost identically opposite. According to Jegadeesh and Titman (2001) price continuation exists over the short and medium term and price reversals occur over the long term, which in the case of their paper was around four to five years after the formation of the strategy. In using weekly data we formed contrarian strategies using holding periods twice as long as those used in weekly momentum strategies, but these holding periods would be considered short term under the terminology of Jegadeesh and Titman (2001). Indeed these weekly strategies have holding periods which are similar to the shortest holding periods in our monthly momentum strategies, which explains why the results are nearly identically opposite.

The similarities between the results of these two strategies can be explained by the length of the time periods used for lookback and holding periods for contrarian strategies. The results from the weekly contrarian strategies therefore do not tell us any more information than the results from the monthly momentum strategies already do, so we move on to the monthly contrarian strategies which cover longer time periods.

5.4 Contrarian (Monthly)

Contrarian monthly strategy results are shown in Table 7. These strategies were created to have longer lookback and holding periods than the monthly momentum strategies. Ideally the maximum lookback and holding periods would be longer than 18 months, however the short time periods covered by the cryptocurrency data mean that this is the maximum length considered. The columns in Table 4.4 list the assets, lookback and holding periods, number of signals generated, and the average returns from these strategies.

The first panel in Table 7 shows the aggregated results across all assets, and the first thing to note about these results is that the total strategies produce returns which are negative for two thirds of the strategies. The only strategies which produce positive total returns are those with an 18-month holding period, and two of these three strategies are statistically significant at the 5 per cent level.

The following five panels break down the returns from these strategies into returns from the individual assets. These results are all very similar to the aggregated results with the majority of returns being negative, and any significant positive total returns coming from strategies with an 18-month holding period.

One reason which can explain the negative returns of most contrarian strategies is that they are not formed over long enough time periods to experience the long term price reversals observed by Jegadeesh and Titman (1993). These long term price reversals are attributed to long term overreactions to positive (negative) news which causes prices to go above (below) some intrinsic value before it reverts back toward this intrinsic value.

The contrarian strategy with the best performance over our observation period was the 9-month / 18-month strategy which produced an average of 10 per cent annual returns. It makes sense that the best performing strategy is the one with the longest holding period, as Jegadeesh and Titman (1993) find that price reversals occur in the long term and not in the short or medium terms.

An interesting trend that can be observed in Table 7 is that increasing the holding period of the contrarian strategy leads to better results. The first panel of Table 7 which contains the aggregate results across all assets shows that increasing the holding period gives higher returns across all lookback periods. When we investigate this trend at the individual asset level, an increased holding period provides higher returns in eight out of the fourteen instances. The 18-month holding period also provides the highest return in nearly 80 per cent of cases; so as the holding period is lengthened, these contrarian strategies become more profitable.

Due to data constraints in cryptocurrency markets the contrarian strategies generated in this paper cover a maximum holding period of 18 months, whereas price reversals in the literature are observed after periods of 48-60 months (Jegadeesh and Titman, 1993). Results from monthly contrarian strategies do find a correlation whereby increasing the length of the holding period improves the contrarian returns, so future research is advised into cryptocurrency markets which uses holding periods greater than 18 months to see if these markets experience the long term price reversals found in traditional financial markets.

The results from contrarian strategies (both weekly and monthly) agree with the research of Caporale and Plastun (2018) who find that contrarian strategies are not profitable in cryptocurrency markets. This disagrees with the paper from Kosc et al (2018) who find a strong contrarian effect in the same markets.

5.5 Moving Average Crossover

Results from the moving average (MA) crossover strategies are summarised in Table 8. The MA strategies used are all variable length MA (VMA) strategies as outlined by Brock et al (1992).The columns in the table list the asset, the MA strategy (as: SMA – LMA (Band)), the number of signals generated, and the annualised returns.

The difference in the number of signals generated across each strategy follows the same pattern as those found by Levich and Thomas (1991) whereby more signals are generated by strategies which are based on shorter term moving averages than longer term moving averages. The use of bands is also seen to reduce the number of signals from each strategy which is to be expected.

In the first panel, the figures for the returns of each strategy represent a weighted average of the annualised returns from each individual asset, whereby the weights used are the lengths of the associated time series' in years. The final column shows total returns for each strategy, and each MA strategy results in positive returns, the most of which are statistically significant according to conventional significance levels.

Detzel et al (2018) find that BTC, XRP and ETH are all predictable when using an MA 5-100 strategy. While this exact strategy was not tested in our research, we do observe high levels of predictability when using both a 1-5 and a 5-20 strategy across these three assets which adds to their finding that MA strategies can be used profitably in cryptocurrency markets.

The use of bands on MA strategies is generally shown to hinder their performance, and despite the largest returns coming from the shortest length MA strategies, the results do not provide a consensus on whether or not shorter moving averages are always better than longer moving averages since the strategies with an LMA of 200-days and 150-days produce similar results.

Individual assets results mostly mimic those from the aggregated panel although have much less statistical significance. There are however two strategies which consistently produce significant positive results; they are the 1-5 (0%) and 5-20 (0%) strategies. The 5-20 (0%) strategy provides the best returns in five out of the six panels from Table 8, and results in an average annual return of 145 per cent across all assets.

5.6 Filter Rules

Table 9 displays the results from the ten filter rules applied to the cryptocurrency markets. The filter sizes used were chosen to replicate those of Levich and Thomas (1991) and Dooley and Schafer (1984). The columns in Table 9 list the assets, the filter sizes, the number of signals, and the average annualised returns.

The number of trades reduces as the filter size gets larger which is to be expected, and the number of buy signals and sell signals for each filter size are roughly the same due to the tandem nature of the strategy; a long trade is always followed by a short sell and vice versa.

The first panel in Table 9 contains the aggregated results from the filter rules across all of the cryptocurrency assets in the study. These filter rules are hugely successful, with every single filter size resulting in total annualised returns which are large and positive, all of which are statistically significant at the 1 per cent level.

The results for each individual cryptocurrency asset have the same characteristics as those of the aggregated total results in the first panel of Table 9. Individual asset total returns are all positive, with 60 per cent being statistically significant, and 50 per cent are significant at the 5 per cent level.

The two smallest filters, 0.5 and 1 per cent, result in the lowest returns on average. This is probably due to the huge volume of trading associated with each rule leading to transaction costs reducing their profitability. Despite this they still produce 93 and 89 per cent average annual returns respectively.

The best results for a filter rule come from the 7.5 per cent filter, which provides an average of 143 per cent returns across all assets. This size of filter represents a balance between the smaller filters which may have their returns reduced via transaction costs, and the larger filters which trade relatively infrequently.

The profitability of filter rules when applied to cryptocurrencies is in contrast to the findings of Fama and Blume (1966) who say that once transaction costs are accounted for, any profits arising from filter rules are wiped out. The filter rules used in this paper incorporate a 0.25 per cent transaction cost on each trade which is in line with cryptocurrency market standards, and the strategies remain profitable. The profitability of these rules does agree with the results of Levich and Thomas (1991) and Dooley and Schafer (1984), albeit the results when applied to cryptocurrencies are much larger than those in the traditional currency markets from the two studies mentioned.

An interesting outlier in these results is the returns from the filter rules applied to LTC. None of the strategies for LTC return results which achieve any meaningful level of statistical significance, which is in contrast to the results from the rest of the individual assets which all have at least half of their strategies showing statistically significant results. Since we cannot say with 90 per cent confidence that filter rules produce returns which are not equal to zero, this is some evidence for the market for LTC being weak form efficient. It is at least evidence that the LTC market is more efficient than the markets for the other cryptocurrencies in this study, which is a point discussed further in section 5.11 of the results.

5.7 Trading Range Break

Trading range break results are summarised in Table 10. The columns list the asset, strategy (number of days in the range and the band), number of signals, average trades per year, average returns from signals, average returns from all trades, and the annualised average returns for the strategy – which is calculated as the average returns per trade multiplied by the average number of trades per year.

The first panel in Table 10 provides the average results for each TRB strategy across all five assets studied, and shows that the average annual return for every strategy was large, positive and statistically significant at the 1 per cent level.

The following five panels in Table 10 split the returns into those from the individual assets; these returns show the same characteristics as the aggregate returns from the first panel. For every asset studied, every strategy results in an average annual return which is large and positive with a high level of statistical significance. In fact, 83 per cent of total returns for individual assets are significant at the 1 per cent level, with the remaining 17 per cent significant at the 5 per cent level.

The best performing TRB strategy is the 50-day strategy with no band. This strategy results in the highest average annual return of 413 per cent, and also gives the highest return in all five individual assets.

An interesting trend to note with TRB strategies is that shorter length strategies provide higher length returns than longer length strategies. For every individual asset studied, the returns from the 50-day range beat those from the 150-day range, which in turn beat those from the 200-day range. This is true when using both the 0 per cent band and the 1 per cent band. This trend is not present in any of the literature which this paper bases its TRB strategies on (Brock et al 1992; Hudson et al 1995; Lento and Gradojevic 2007).

Another trend to note about these strategies is that the imposition of a band on the trading strategy consistently results in lower average annual returns. This is the case in fourteen out of the fifteen strategies tested at the asset level. This is in contrast to the findings of Brock et al (1992) who observe an improvement in returns with the use of a 1 per cent band. The papers from Hudson et al (1995) and Lento and Gradojevic (2007) do not provide the results for strategies that implement any bands.

5.8 Differences in Returns from Buy and Sell Signals

For momentum (contrarian) and TRB strategies, there are more buy (sell) signals generated than sell (buy) signals which is noted by Brock et al (1992) to indicate that the underlying time series is upward sloping. The filter rules and MA strategies do not show this due to the design of these strategies; a buy signal can only be followed by a sell signal and vice versa, so the number of buy and sell signals for these strategies are very close.

More insight is gained into the structure of the returns from the strategies by separating them into returns following buy signals and returns following sell signals. Buy signals for all strategies consistently generate large, positive returns which have high degrees of statistical significance. Sell signals on the other hand generate returns which are lower in magnitude and mostly negative (aside from filter rules where these returns are positive but close to zero), and have lower levels of statistical significance.

Contrarian strategies result in different characteristics for buy and sell returns due to their design. Buy returns for contrarian strategies still generate significant positive returns and sell signals generate significant negative returns, but the negative returns from these selling signals are nearly all of greater magnitude than the returns from buy signals. The reason for this is that the contrarian strategies implemented in this research do not cover long enough holding periods to observe the price reversals found in previous research (Jegadeesh and Titman, 1993). Therefore the returns from contrarian strategies are similar in structure to the returns from momentum strategies; returns following a buy (sell) signal for momentum (contrarian) strategies are greater in magnitude than returns following a sell (buy) signal.

Across all average strategies, every positive signal results in a positive return, 99 per cent of which are statistically significant. 81 per cent of negative signals meanwhile result in negative returns, and 67 per cent of these are significant. This supports the findings of Brock et al (1992) who note that MA buy signals produce better returns than MA sell signals.

The evidence from this research shows that the technical trading strategies tested demonstrate the ability to efficiently predict upwards price movements in cryptocurrencies since the assets studied all experience forms of price momentum after buy signals are generated. These strategies however are unable to predict downwards price movements as evidenced by the negative returns following sell signals, in fact these strategies seem to predict some small amounts of price reversal following sell signals.

5.9 Implications for Market Efficiency

For a market to be weak-form efficient, previous prices and previous price changes must have no relationship with current and future prices. A market which is said to be weak-form efficient has price changes which follow a random walk and are not related to each other.

Our results reject the notion that cryptocurrency markets are weak form efficient. Returns following buy signals are large, positive and significant while returns following sell signals are mostly negative and significant. The strategies tested can consistently generate excess returns following buy signals but not following sell signals. Since future price rises can be predicted with these strategies the market is not weak form efficient, despite future price drops being seemingly unpredictable.

It may be suggested that this declaration of a lack of market efficiency is an overstatement, and that the large positive returns of long strategies can be attributed to the explosive nature of the underlying time series' used to test the trading strategies. Each one of the assets studied has experienced a vast rise in price over the course of the period observed. The result of this is that no matter what previous trend or signal is detected, the price continued to trend upward throughout the length of the study, which would result in positive returns for every long strategy and negative returns for every short strategy.

However, if the returns from the trading strategies studied could be solely attributed to the explosive nature of the underlying time series', then the returns following long strategies would be expected to be similar in magnitude to the returns following short strategies and this is not the case. Excluding contrarian strategies, returns following buy signals are greater in magnitude than returns following that strategy's respective sell signals in 89 per cent of cases with respect to both average and individual asset strategies. Since the magnitude of returns following buy signals are nearly all greater than the magnitude of returns following sell signals, the hypothesis that the positive returns observed can be solely attributed to the large upward trends in the underlying time series' is rejected. Therefore, we can still say that the cryptocurrency markets studied are not weak form efficient.

These results oppose the findings of Nadarajah and Chu (2017), Jiang et al (2017) and Tiwari et al (2018) who all state that the market for BTC satisfies weak form market efficiency. However this declaration of a lack of market efficiency in cryptocurrency markets agrees with research by Urquhart (2016), Bariviera (2017) and Kristoufek (2018) who all find that the market for BTC is not weak form efficient, as well as Caporale et al (2018) who find that the markets for BTC, LTC and XRP are not weak form efficient.

5.10 Comparison of Results across Strategies

To compare the performance of the different types of technical trading strategies which have been implemented, Table 11 lists the performance of the top three individual strategies from each overall strategy type.

The best performance by far comes from the TRB strategies, whereby even the third best of these strategies, the 50-Day trading range with a 1 per cent band, yields more than double the amount of average annual return than the top performer in every other category.

Filter rules and MA strategies produce fairly similar results, both provide large and positive annual returns. Weekly momentum strategies outperform monthly momentum strategies, while weekly contrarian strategies provide negative returns and monthly contrarian strategies produce very small positive returns only at the longest holding periods.

Most contrarian strategies result in negative returns. The reason for this as suggested previously is that they do not utilise long enough holding periods to experience the price reversal suggested by Jegadeesh and Titman (1993).

The imposition of a band on MA and TRB strategies is shown to reduce their performance. This result disagrees with the findings of Brock et al (1992) who note the improvements gained by strategies which use a 1 per cent band over those which do not use a band at all.

Table 12 shows the individual assets which provided the highest and the median levels of annual return for the top performing strategy from each technical trading strategy type. Returns for the median strategies are used here to reduce possible bias from any outliers from the results, for example the 16-week / 12-week contrarian weekly results for XRP which had an average annual return of 110 per cent, when this strategy returned an average of -30 per cent annually across all assets.

Figure 1 plots the returns of the median performing assets for the top strategies over time (excluding the contrarian strategies). From this figure we can see the consistent positive returns generated by each strategy, and can see that the 50-Day (0%) TRB strategy greatly outperforms all others, with the monthly momentum strategy providing the least returns.

The 50-Day (0%) TRB strategy provides the highest annual return, and also has the highest Sharpe Ratio. Excluding contrarian strategies, the rest of the top performing strategies all produce large Sharpe Ratios, indicating that their excess returns are not simply accounted for by excess risk.

5.11 Comparison of Results across Assets

To observe the difference in performance between each individual cryptocurrency asset, the average annual returns across all strategies are calculated and plotted in Figure 2**.** This figure shows that the highest average annual return comes from the technical trading strategies applied to ETH, which averages returns of over 112 per cent annually. The lowest annual returns are given by LTC, with an average of just under 45 per cent annually, however these returns are still positive.

The average returns for the CRIX are a proxy for the cryptocurrency market in general, showing that the market itself is not weak form efficient, due to the excess returns generated by technical trading strategies on average.

Whilst the returns for BTC and LTC are lower than the market index, these returns are still positive which indicates that the markets for these assets do not satisfy the definition of weak form market efficiency.

One reason that BTC and LTC provide the two lowest average annual returns could be that these markets are becoming more efficient over time. This is suggested by Urquhart (2016) and Caporale et al (2018) who state that BTC and LTC respectively are becoming more efficient over time, possibly due to competition driving the market towards efficiency as investors compete for profits from technical trading strategies such as the ones tested in this paper.

5.12 Robustness Checks

5.12.1: Transaction Costs Increased to 1 per cent

As mentioned previously, the most popular cryptocurrency exchanges typically charge a transaction fee of between 0.1 and 0.3 per cent per trade and for this reason the main results section calculated the results using a 0.25 per cent transaction costs.

This 0.25 per cent value used does not consider any charges incurred when an investor deposits fiat money into an exchange to purchase cryptocurrencies however, so typically there will be some extra amount charged. This is a one-off cost and not a recurring cost to trading and so was not considered in calculations however it will add some cost to investing.

Likewise, exchanges usually charge a withdrawal cost if an investor wished to take their fiat money out of the exchange. This cost was also not considered in calculations, yet will add some cost to investing.

The 0.25 per cent value used also did not consider transaction costs associated with a lack of market depth. The results section assumes that all trades are transacted at the current asset price on a given date as reported by CoinMarketCap, however if there is not a large quantity of assets available at this depth then the trade will be carried out at an inferior price. Since this research does not take market volume or hypothetical trade sizes into consideration this effect was not directly accounted for, though the use of a larger transaction cost can attempt to account for this.

To attempt to account for the aforementioned transaction costs that were not previously considered, we repeat the same strategies over the same datasets although the transaction cost applied to each trade is increased from 0.25 per cent to 1 per cent. This higher value is more than enough to account for the new costs which have been mentioned.

To compare results using different transaction costs, tables 13 to 19 show the results for average strategy returns for the same seven trading strategy types used originally, only now with a 1 per cent rather than a 0.25 per cent transaction cost per trade. These tables are laid out similarly to the original tables, and now also contain an extra column which shows the difference between the returns using a 0.25 per cent and a 1 per cent transaction cost. Returns at the individual asset level are not reported to save space as the comparisons are only drawn between average results.

An increase in transaction costs will have a disproportionately adverse effect on trading strategies which conduct more trades. For this reason, in Tables 13 to 16 we can see that the returns of momentum and contrarian strategies are not changed much after the increase in transaction costs. Weekly momentum strategies suffer the greatest reductions in returns out of these four strategies, with the other three strategies showing an average difference of only 2 per cent in returns.

Tables 17 to 19 list the respective returns for MA, Filter and TRB strategies following an increase in transaction costs. We can see within each of these tables how strategies that conduct more trades suffer more from increasing transaction costs, shorter moving average and trading range lengths, and lower filter sizes all correlate with a higher difference in returns after transaction costs are increased.

The profits of the 1-5 MA strategy are completely wiped out by increasing transaction costs and it now produces a loss of 12 per cent annually, the 5-20 MA strategy still produces the largest returns of any despite a significant reduction.

Every filter strategy with a filter size less than or equal to five suffers a complete obliteration of previously positive returns, the only remaining profitable filter strategies are those with a filter of at least 7.5 per cent. The top performing filter strategy is now the 20 per cent filter, while the 7.5 per cent filter still results in large significant returns.

The TRB strategies all show substantial reductions in annual returns, yet these strategies still produce large significant returns. The 50-day trading range strategy with no band had the largest reduction in annual return of 79 per cent, yet still resulted in the highest returns across the six strategies.

Overall, an increase in transaction costs for these strategies does not significantly reduce their profitability. The MA 1-5 strategy and the filter sizes of 5 or less suffered the worst, but aside from these six strategies all other 49 previously profitable strategies remained profitable. This result is in contrast to the findings of Caporale and Plastun (2018) who state that transaction costs can eradicate any profitability from momentum strategies in cryptocurrency.

5.12.2 Results during the 2018 Downturn

The results so far show that returns following buy signals are significantly more profitable than the returns following sell signals. It could be suggested that a lot of the success of the strategies tested in this paper stems from the huge increases in cryptocurrency prices of the length of the data, particularly in 2017.

The cryptocurrency markets however suffered large losses during the first five months of 2018, losing nearly 40 per cent of total value. The total market capitalisation as listed by CoinMarketCap (2018b) dropped from $5.7 billion to $3.4 billion between the 31st of December 2017 and the 3rd of June 2018.

This downturn period provides us with a natural economic experiment to test whether or not the trading strategies which we have identified as being profitable over the full time period studied remain profitable during a period of large losses. This section provides the results from all trading strategies at the average level for those strategies which were active during 2018 only, and the results are presented in Tables 20 to 26.

The results during 2018 are mixed across the different strategies, almost all weekly momentum strategies produce lower returns and only the 2-week / 8-week strategy retains any significant positive returns. Monthly momentum strategies on the other hand nearly all see an increase in performance, especially those with a six month holding period. Contrarian weekly strategies do not experience much change and the contrarian monthly strategies all perform marginally worse.

The most interesting results from this sub period are those from the MA strategies and filter rules. Every single MA strategy tested performed significantly better in 2018 during a period of large losses, with the relatively longer length MA strategies achieving larger increases in performance. The 5-150 strategy provided the largest returns with an annual return of over 700 per cent.

Filter rules display similar results to the MA strategies; 80 per cent of the filter sizes show higher annual returns for 2018 than all other years, with the two smallest filter sizes suffering a reduction in returns whilst remaining positive. The 20 per cent filter shows the largest gain in returns and had the best performance in 2018 with an annual return of nearly 300 per cent.

The large positive returns from MA strategies are all provided by the buy signals, which still outperform the returns following sell signals despite the trend of the underlying time series' to be significantly downward. Filter rules are the opposite, returns following a sell signal for filter rules are all large, positive and statistically significant and the returns following buy signals are all lower and lack any significance. This makes more sense intuitively as the underlying time series' which the rules are based on is trending downwards.

Despite improved performance for MA and filter strategies, TRB strategies all suffer a complete reversal in their returns during the 2018 downturn. Table 26 shows that every length of trading range with and without a band produced annualised losses of at least 140 per cent which were mostly a result of buy signals being generated during the downturn. Unfortunately the 150 and 200-day trading ranges were too long to produce any sell signals during 2018 which is where these strategies would be expected to profit.

The overall results suggested that the 50-day TRB strategy provides the highest returns out of all the strategies we tested, however upon observing the returns of the strategies during the 2018 downturn in the cryptocurrency markets we can say that this is no longer the top performing strategy due to the losses incurred from TRB strategies during a downturn.

It could be the case that TRB strategies which utilise shorter trading ranges will perform better in cryptocurrency markets than the TRB strategies tested in this paper. The volatility in cryptocurrency markets can result in extreme price changes over short periods of time, and a shorter trading range can react relatively quicker to these changes than a longer trading range can.

Future research into these strategies in cryptocurrency markets should therefore test strategies with trading ranges less than 50 days.

Moving average strategies and filter rules are considered to outperform the TRB strategies as they both deliver positive returns during the 2018 downturn, as well as large positive returns over the whole observation period. The top performing strategy can now be considered to be either the 5-20 MA strategy, or the 7.5 per cent filter rule. Over the full observation period, these two strategies result in 145 and 143 per cent annual returns respectively, as well as averaging 310 and 146 per cent returns respectively during the 2018 downturn.

Figure 3 plots the cumulative returns of the top performing strategy from four of the overall strategies (contrarian returns are excluded) for CRIX against returns of CRIX itself over the length of the downturn period. CRIX is used to provide a proxy for the cryptocurrency markets as a whole, as we have seen that the individual cryptocurrencies studied have differing levels of market efficiency and so produce different results for the technical trading strategies employed. This chart shows that while CRIX experienced significant losses, the monthly momentum strategy, MA strategy and filter rule all produced positive returns.

6. CONCLUSION

In conclusion, this research shows that the four cryptocurrency markets studied (BTC, LTC, XRP and ETH) as well as the cryptocurrency market as a whole (via the index CRIX) are not weak form market efficient. This is evidenced through the large and statistically significant returns which are generated from momentum strategies (both weekly and monthly), moving average (MA) strategies, filter rules, and trading range break (TRB) strategies. In total, over 70 per cent of strategies tested result in average annual returns which are positive and significant.

Due to data constraints in the cryptocurrency market, the longest holding periods tested for any contrarian strategy are 18-months long, despite evidence from the literature (Jegadeesh and Titman, 1993) suggesting these strategies are profitable at much longer time periods of around 48-60 months. For this reason, the contrarian strategies tested produce significant losses, however increasing the holding period on monthly strategies is shown to increase returns.

The lack of market efficiency observed in this research agrees with previous findings from Urquhart (2016), Bariviera (2017), Jiang, Nie and Ruan (2017) and Kristoufek (2018) with regards to BTC, as well as findings from Caporale and Plastun (2018) with regards to LTC and XRP. According to Urquhart (2016) and Bariviera (2017) BTC is improving in market efficiency over time, likewise Caporale and Plastun (2018) find the same can be said for LTC. These two assets are shown to produce the least average annual returns across all of the technical trading strategies tested, this could be due to their efficiency improving over time and eradicating profits from strategies which rely on a lack of weak form market efficiency.

By separating strategy returns into those following a buy signal and those following a sell signal, it is shown that the positive returns from the trading strategies are not simply due to the vast rises in cryptocurrency prices observed over the period of the study. If this were true, sell signals would result in negative returns of a similar magnitude to the positive returns which follow buy signals. Our results show this is not the case, as buy signals generate returns larger in magnitude than those following selling signals.

To account for indirect costs of trading such as a lack of market depth and deposit/withdrawal fees, the transaction cost per trade is increased from 0.25 per cent to 1 per cent. After this rise in transaction costs, 80 per cent of strategies are shown to retain their statistically significant positive returns, demonstrating their robustness. This result disagrees with the findings of Caporale and Plastun (2018) who believe the imposition of transaction costs would eradicate the profitability of the momentum strategies which they tested. We show that this is not the case as most strategies retain their profitability after a large increase in transaction costs.

As a further robustness test, the returns for the trading strategies that take place only in the 2018 calendar year are presented to take advantage of a natural experiment; testing how well the strategies perform during a downturn period. The 2018 results show that TRB strategies suffered enormous losses during the downturn, and it is suggested that this may be in part due to the length of the trading ranges used.

During this downturn period however, monthly momentum strategies, MA strategies and filter rules all see significant improvements in performance. This shows that their significant returns are robust to market downturns and cannot be simply attributed to the price rises experienced in the cryptocurrency markets before 2018.

Taking into account the 2018 downturn period as well as the possibility of higher transaction costs, the best results come from MA strategies and filter rules. The best single strategy is either the 5-20 MA strategy with no band or the 7.5 per cent filter rule. Both of these strategies produce large returns pre-2018 as well as large returns during the 2018 downturn, returning respective averages of 145 and 143 per cent annually across the whole observation period.

Despite the cryptocurrency assets studied demonstrating extreme levels of volatility throughout the length of the study, the Sharpe Ratios for the median performing MA 5-20 strategy and 7.5 per cent filter rule are 1.52 and 1.5 respectively. These figures indicate that the large excess annual average returns provided by these two strategies are not simply compensation for assuming excess risk.

There are excess returns to be made by actively trading in cryptocurrency markets using some simple technical trading strategies, as shown by the results in this paper. While it is up to the individual investor to decide which strategy works best for them, our evidence points to a 5-20 MA strategy or a 7.5 per cent filter rule resulting in the best average annual returns.

Future research in this area should test contrarian strategies with holding periods closer to 48-60 months when the data is available in cryptocurrency markets to observe whether the price reversals noted in traditional markets occur in these markets also.

Future research should also test TRB strategies with ranges shorter than 50-days as these will react quicker to extreme price changes, reducing the negative returns during a downturn. These shorter TRB strategies may be more appropriate for a market as volatile as that of cryptocurrencies.

7. APPENDIX

Table 1: Summary of relevant literature (Part 1/2)

Year	Author	Focus	Asset(s) Studied	Time period studied	Models / Frameworks	Findings
1966	Fama and Blume	Filter rules	30 stocks on the DJIA	1956 - 1962	24 different filters between 0.5 percent and 50 percent	Filter rules were outperformed by the buy and hold strategy, without accounting for transaction costs
1967	Van Horne & Parker	Moving average strategies	30 random industrial stocks from the NYSE	1960 - 1966	100, 150 and 200 days rules, with 0, 2, 5, 10, and 15 percent bands	Do not outperform the buy and hold strategy
1968	James	Moving average strategies	Month-end stock prices on the NYSE	1926 - 1960	Uses a simple moving average and an exponentially weighted moving average over a six month period, with 2 and 5 percent bands respectively.	Do not outperform the buy and hold strategy
1970	Jenson and Bennington	Levy (1967) 'relative strength trading rule'	Month-end stock prices on the NYSE	1926 - 1966	Replicates the research by Levy (1967)	These rules were outperformed by the buy and hold strategy for all but two of the securities
1985	DeBondt & Thaler	Contrarian strategies	Month-end stock prices on the NYSE	1926 - 1982	1, 2, 3, and 5 year lookback periods with 1, 12, 13, 18, 24, 25, 36, and 60 month holding periods	Loser portfolios outperform winner portfolios 36-months after formation
1991	Levich and Thomas	Filter rules and moving average rules	Futures contracts on foreign exchange markets	1976 - 1990	0.5, 1, 2, 3, 4, and 5 percent filters and 1/5, 5/20, and 1/200 day moving averages	Profitable, however declining as time passes
1992	Brock, Lakonishok and LeBaron	Moving average and trading range break rules	Dow Jones Index	1897 - 1986	1/50, 1/150, 5/150, 1/200, and 2/200 day moving averages, and 50, 150, and 200 day trading ranges	Both generate excess returns. For MA rules, buy signals generate higher returns than sell signals
1993 & 2001	Jegadeesh & Titman	Momentum and Contrarian returns	Centre for Research in Security Prices returns file	1965 - 1989	1, 2, 3, and 4 quarter lookback and holding periods	Buying winners and selling losers generates excess returns
1994	Lakonishok et al	Contrarian Strategies	NYSE and AMEX stocks	1963 - 1990	5 year lookback and up-to 5 year holding periods	Buying losers outperforms buying 'glamour' (winner) stocks
1995	Hudson, Dempsey and Keasey	Moving average and trading range break rules	30 UK stocks	1935 - 1994	1/50, 1/150, 5/150, 1/200, and 2/200 day moving averages, and 50, 150, and 200 day trading ranges	Trading rules have predictive ability but unlikely to outperform buy and hold in the presence of trading costs.
1998	Rouwenhorst	Momentum strategies	2,190 stocks across 12 European markets	1978 - 1995	1, 2, 3, and 4 quarter lookback and holding periods	Winners outperform losers
1999	Shiereck et al	Momentum and Contrarian returns	357 companies on Frankfurt Stock Exchange	1961 - 1991	1, 3, 6, and 12-month lookback and holding periods for momentum. Five year lookback and holding period for contrarian.	Strategies outperformed an investment in the stock market index
2002	Hameed and Kusnadi	Momentum strategies	Monthly stock returns across six Asian markets	1979 - 1994	1, 2, 3, and 4 quarter lookback and holding periods	No evidence of momentum in Asian stock markets
2003	Forner and Marhuenda	Momentum and Contrarian returns	Monthly returns of Spanish stock market stocks	1963 - 1997	6, 12, 36, and 60 month lookback and holding periods	12 month momentum and five year contrarian strategies yield significantly positive returns
2003	Hurn and Pavlov	Momentum strategies	Monthly returns of the top 200 Australian stocks	1973 - 1998	6-month lookback with holding periods between 1 and 36 months	Existence of short to medium term momentum

Table 1: Summary of relevant literature (Part 2/2)

Year	Author	Focus	Asset(s) Studied	Time period studied	Models / Frameworks	Findings
2004	Mengoli	Momentum strategies	332 Stocks listed on the Milan Stock Exchange	1950 - 1995	1, 2, 3, and 4 quarter lookback and holding periods	Momentum strategies are profitable in the medium term (3-12 months)
2007	Muga and Santamaria	Momentum strategies	Stocks in four Latin American indices	1994 - 2005	1, 2, 3, and 4 quarter lookback and holding periods	Momentum strategies yield profits in Latin American emerging markets
2007	Lento and Gradojevic	Moving average, filter rules, and trading range break rules	Three indices and the CAD/USD spot rate	1995 - 2004	1/50, 1/200, and 5/150 day moving averages, 1, 2, and 5 percent filters, and 50, 150 , and 200 day trading ranges	Moving average and trading range break rules can generate excess returns, and in some cases filter rules may be useful.
2010	Szakmary, Shen and Sharma	Moving average strategies	Commodity futures markets	1959 - 2007	Short term moving averages are 1 or 2 months whilst long term moving averages are 6 or 12 months.	Profitable (net of transaction costs) in at least 22/28 markets
2012	Moskowitz, Ooi and Pedersen	Momentum strategies	Equity index, currency, commodity and bond futures	1965 - 2009	Time Series Momentum (TSMOM) with lookback & holding periods up to 48 months	TSMOM returns are significant and consistent across nearly all futures contracts studied
2016	Urquhart	Weak form market efficiency	Bitcoin	2010 - 2016	Ljung-Box test, Runs test, Bartels test, AVR test, BDS test, and R/S Hurst component	Bitcoin market is not weak form efficient, but is becoming more efficient over time
2017	Nadarajah and Chu	Weak form market efficiency	Bitcoin	2010 - 2016	Raise Bitcoin returns to the power of 17 before applying the statistical tests from Urquhart (2016)	Bitcoin market is weak form efficient
2017	Bariviera	Weak form market efficiency	Bitcoin	2011 - 2017	Hurst R/S and Hurst DFA	Bitcoin market is not weak form efficient from 2010 to 2014, but is weak form efficient from 2014 onwards
2017	Jiang, Nie and Ruan	Weak form market efficiency	Bitcoin	2010 - 2017	Generalised Hurst exponents	Bitcoin market has a high degree of inefficiency, and is not improving over time
2018	Kristoufek	Weak form market efficiency	Bitcoin	2010 - 2017	Kristoufek & Vosvrda (2013) 'Efficiency Index'	Bitcoin market is mostly inefficient from 2010 to 2017, but shows periods of efficiency after bubble-like price surges
2018	Tiwari et al	Weak form market efficiency	Bitcoin	2010 - 2017	Series of long-range dependence estimators	Bitcoin returns are weak form efficient apart from two short time periods
2018	Caporale, Gil-Alana and Plastun	Weak form market efficiency	Bitcoin, Litecoin, Ripple, Dash	2013 - 2017	R/S Analysis and Fractional integration	All four cryptocurrencies are not weak form efficient, whilst Litecoin is improving in efficiency over time
2018	Caporale and Plastun	Momentum and Contrarian strategies	Bitcoin, Litecoin, Ripple, Dash	2013 - 2017	ANOVA, regression analysis, and Mann-Whitney U test	Contrarian strategies unprofitable, momentum strategies have predictive ability but may not be possible due to transaction costs
2018	Kosc, Sakowski and Slepaczuk	Momentum and Contrarian strategies	100 Cryptocurrencies with highest market caps	2014 - 2017	1 week lookback for momentum and contrarian strategies	Find a strong daily contrarian effect and a lack of a momentum effect
2018	Detzel et al	Moving average strategies	Bitcoin	2010 - 2018	1/5, 1/10, 1/20, 1/50, and 1/100 day moving average strategies are used	Moving average strategies outperform the buy and hold, and provide a higher Sharpe ratio with lower drawdown.

Table 2: Summary Statistics for Daily Returns of All Assets

Returns are measures as log differences in the price of the asset each day; N is the total number of daily observations of each asset.

Name	Start Date	N	Mean	Standard Deviation	Skew	Kurtosis
Bitcoin (BTC)	01 June 2013	1827	0.00223	0.0447	-0.167	7.96
Litecoin (LTC)	01 June 2013	1827	0.00205	0.0691	1.798	25.34
Ripple (XRP)	04 August 2013	1763	0.00265	0.0797	2.007	26.93
Ethereum (ETH)	09 August 2015	1028	0.00645	0.0715	0.521	4.42
Crypto Index (CRIX)	31 July 2014	1400	0.00226	0.0390	-0.717	6.59

Table 3: Moving Average Crossover Strategies

SMA is the shorter moving average, LMA is the longer moving average, and the band is the percentage the LMA must be exceeded by in order to generate a buy or a sell signal.

SMA (Days)	LMA (Days)	Band (%)
1	5	0%
5	20	0%
1	50	0%
1	50	1%
1	150	0%
1	150	1%
5	150	0%
5	150	1%
1	200	0%
1	200	1%
2	200	0%
2	200	1%

Table 4: Momentum (Weekly) Returns Part 1/2

The first panel contains the average results across all assets; the following five panels contain the results at the asset level. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Lookback (Weeks)	Holding (Weeks)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All		2	572	520	**1092**	2.31***	0.31	**1.36*** **
	2	4	565	517	**1082**	1.95***	-0.19	**0.93*** **
		8	551	511	**1062**	1.71***	-0.47***	**0.66*** **
		2	585	499	**1084**	2.00***	-0.05	**1.05*** **
	4	4	575	499	**1074**	1.84***	-0.30	**0.84*** **
		8	568	486	**1054**	1.66***	-0.53***	**0.65*** **
		2	612	454	**1066**	1.77***	-0.22	**0.92*** **
	8	4	605	451	**1056**	1.81***	-0.26	**0.92*** **
		8	605	431	**1036**	1.56***	-0.57***	**0.67*** **
BTC		2	145	111	**256**	1.67***	0.18	**1.02*** **
	2	4	144	110	**254**	1.39***	-0.30	**0.66*** **
		8	141	109	**250**	1.29***	-0.45*	**0.53*** **
		2	151	103	**254**	1.35***	-0.28	**0.69*** **
	4	4	149	103	**252**	1.30***	-0.40	**0.60*** **
		8	148	100	**248**	1.35***	-0.30	**0.68*** **
		2	161	89	**250**	1.37***	0.06	**0.90*** **
	8	4	159	89	**248**	1.48***	0.15	**1.00*** **
		8	159	85	**244**	1.38***	0.00	**0.90*** **
LTC		2	122	130	**252**	2.24***	0.61	**1.40*** **
	2	4	121	129	**250**	1.84***	0.17	**0.98*** **
		8	118	128	**246**	1.38***	-0.26	**0.53** **
		2	125	127	**252**	1.84***	0.19	**1.01** **
	4	4	123	127	**250**	1.63***	-0.03	**0.79** **
		8	122	124	**246**	1.21***	-0.49	**0.36**
		2	118	132	**250**	2.10***	0.36	**1.18*** **
	8	4	118	130	**248**	1.88***	0.13	**0.96*** **
		8	118	126	**244**	1.26***	-0.45	**0.38**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 4: Momentum (Weekly) Returns Part 2/2

Asset	Lookback (Weeks)	Holding (Weeks)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
XRP		2	99	148	**247**	2.76***	0.14	**1.19** **
	2	4	98	147	**245**	2.13***	-0.30	**0.67**
		8	95	146	**241**	1.80***	-0.44	**0.45**
		2	106	139	**245**	2.79**	0.36	**1.41*** **
	4	4	104	139	**243**	2.26***	0.02	**0.98** **
		8	102	137	**239**	1.83***	-0.34	**0.59***
		2	114	127	**241**	1.79**	-0.14	**0.77**
	8	4	112	127	**239**	1.70**	-0.35	**0.61**
		8	112	123	**235**	1.12**	-0.86**	**0.08**
ETH		2	84	58	**142**	4.25***	0.62	**2.76*** **
	2	4	82	58	**140**	3.78***	-0.40	**2.05*** **
		8	79	57	**136**	3.48***	-1.16**	**1.54*** **
		2	84	56	**140**	3.33***	-0.98	**1.61*** **
	4	4	82	56	**138**	3.36***	-1.28**	**1.48*** **
		8	80	54	**134**	3.14***	-1.79***	**1.15*** **
		2	94	42	**136**	2.97***	-1.85**	**1.48** **
	8	4	92	42	**134**	3.15***	-1.65**	**1.65*** **
		8	92	38	**130**	3.02***	-1.76***	**1.62*** **
CRIX		2	122	73	**195**	1.45***	0.07	**0.93*** **
	2	4	120	73	**193**	1.33***	-0.29	**0.72*** **
		8	118	71	**189**	1.30***	-0.40*	**0.66*** **
		2	119	74	**193**	1.34***	-0.22	**0.74*** **
	4	4	117	74	**191**	1.28***	-0.47	**0.60*** **
		8	116	71	**187**	1.38***	-0.37	**0.71*** **
		2	125	64	**189**	1.05***	-0.88*	**0.39***
	8	4	124	63	**187**	1.28***	-0.55	**0.66*** **
		8	124	59	**183**	1.38***	-0.33	**0.83*** **

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 5: Momentum (Monthly) Returns Part 1/2

The first panel contains the average results across all assets; the following five panels contain the results at the asset level. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Lookback (Months)	Holding (Months)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All	3	3	152	83	**235**	0.93***	-1.22***	**0.17**
		6	142	78	**220**	1.28***	-0.93***	**0.50*** **
		9	127	78	**205**	0.86***	-0.82***	**0.22***
		12	114	76	**190**	0.88***	-0.75***	**0.23****
	6	3	153	67	**220**	0.90***	-0.75*	**0.39***
		6	138	67	**205**	1.32***	-0.81***	**0.63*****
		9	124	66	**190**	0.89***	-0.78***	**0.31****
		12	109	66	**175**	0.96***	-0.67***	**0.35*****
	9	3	149	56	**205**	0.96***	-1.15***	**0.39***
		6	134	56	**190**	1.37***	-1.16***	**0.62*****
		9	119	56	**175**	1.02***	-0.85***	**0.42*****
		12	104	56	**160**	1.01***	-0.86***	**0.36*****
	12	3	140	50	**190**	1.13***	-1.00**	**0.57****
		6	125	50	**175**	1.73***	-0.63***	**1.05*****
		9	110	50	**160**	1.19***	-0.72***	**0.59*****
		12	95	50	**145**	1.10***	-0.85***	**0.43*****
BTC	3	3	39	17	**56**	1.11***	-0.11	**0.74****
		6	38	15	**53**	1.17***	0.07	**0.86*****
		9	35	15	**50**	0.74***	-0.16	**0.47*****
		12	32	15	**47**	0.55***	-0.18	**0.32****
	6	3	37	16	**53**	0.82***	0.39	**0.69*****
		6	34	16	**50**	1.17***	0.20	**0.86*****
		9	31	16	**47**	0.74***	0.00	**0.49*****
		12	28	16	**44**	0.54***	-0.15	**0.29****
	9	3	36	14	**50**	0.89***	0.04	**0.65*****
		6	33	14	**47**	1.13***	-0.11	**0.76*****
		9	30	14	**44**	0.73***	-0.30	**0.40****
		12	27	14	**41**	0.56***	-0.41**	**0.23***
	12	3	34	13	**47**	0.72**	-0.32	**0.43***
		6	31	13	**44**	1.10***	-0.45**	**0.64*****
		9	28	13	**41**	0.73***	-0.57***	**0.32***
		12	25	13	**38**	0.58***	-0.66***	**0.16**
LTC	3	3	28	28	**56**	0.56	-1.10	**-0.27**
		6	26	27	**53**	1.16***	-0.36	**0.39**
		9	23	27	**50**	0.50	-0.36	**0.03**
		12	20	27	**47**	0.56	-0.24	**0.10**
	6	3	35	18	**53**	0.53	0.10	**0.38**
		6	32	18	**50**	0.81**	-0.24	**0.43**
		9	29	18	**47**	0.38	-0.26	**0.14**
		12	26	18	**44**	0.35	-0.37	**0.05**
	9	3	35	15	**50**	0.55	-0.49	**0.24**
		6	32	15	**47**	0.92**	-0.49	**0.47**
		9	29	15	**44**	0.53	-0.53*	**0.17**
		12	26	15	**41**	0.57*	-0.54**	**0.17**
	12	3	35	12	**47**	0.75	-0.34	**0.47**
		6	32	12	**44**	1.15***	-0.52	**0.70****
		9	29	12	**41**	0.77**	-0.59**	**0.38**
		12	26	12	**38**	0.85***	-0.57**	**0.40***

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 5 Momentum (Monthly) Returns Part 2/2

Asset	Lookback (Months)	Holding (Months)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
XRP	3	3	31	22	**53**	-0.30	-2.00**	**-1.00***
		6	29	21	**50**	0.84	-1.69**	**-0.22**
		9	26	21	**47**	0.42	-1.17***	**-0.29**
		12	25	19	**44**	0.61*	-1.37***	**-0.24**
	6	3	28	22	**50**	0.44	-1.66*	**-0.48**
		6	25	22	**47**	1.69***	-1.31**	**0.29**
		9	23	21	**44**	0.72	-1.25***	**-0.22**
		12	20	21	**41**	1.23***	-0.88**	**0.15**
	9	3	27	20	**47**	0.41	-2.30**	**-0.74**
		6	24	20	**44**	1.31**	-2.16***	**-0.27**
		9	21	20	**41**	0.71	-1.26***	**-0.25**
		12	18	20	**38**	0.98**	-1.25***	**-0.19**
	12	3	24	20	**44**	0.83	-1.80*	**-0.37**
		6	21	20	**41**	2.49***	-0.73	**0.92***
		9	18	20	**38**	1.15**	-0.82*	**0.11**
		12	15	20	**35**	1.18**	-1.14**	**-0.15**
ETH	3	3	23	6	**29**	1.93**	-4.10*	**0.68**
		6	21	5	**26**	1.87***	-5.18**	**0.51**
		9	18	5	**23**	1.50***	-4.36***	**0.22**
		12	15	5	**20**	2.00***	-3.20***	**0.70**
	6	3	23	3	**26**	1.21	-5.95*	**0.38**
		6	20	3	**23**	1.57***	-6.57***	**0.51**
		9	17	3	**20**	1.49***	-4.79***	**0.55**
		12	14	3	**17**	2.11***	-3.49***	**1.12***
	9	3	22	1	**23**	1.52*	-7.37	**1.13**
		6	19	1	**20**	2.21***	-7.23	**1.74****
		9	16	1	**17**	2.17***	-4.85	**1.75*****
		12	13	1	**14**	2.45***	-3.62	**2.02*****
	12	3	20	0	**20**	2.08**	0.00	**2.08****
		6	17	0	**17**	3.02***	0.00	**3.02*****
		9	14	0	**14**	2.50***	0.00	**2.50*****
		12	11	0	**11**	2.39***	0.00	**2.39*****
CRIX	3	3	31	10	**41**	1.53***	-0.04	**1.15*****
		6	28	10	**38**	1.57***	-0.20	**1.10*****
		9	25	10	**35**	1.36***	-0.56	**0.81*****
		12	22	10	**32**	1.21***	-0.60***	**0.64*****
	6	3	30	8	**38**	1.59***	-0.51	**1.15*****
		6	27	8	**35**	1.60***	-0.60**	**1.10*****
		9	24	8	**32**	1.45***	-0.77***	**0.89*****
		12	21	8	**29**	1.26***	-0.76***	**0.71*****
	9	3	29	6	**35**	1.64***	-0.73	**1.23*****
		6	26	6	**32**	1.64***	-0.88***	**1.17*****
		9	23	6	**29**	1.48***	-0.91***	**0.99*****
		12	20	6	**26**	1.29***	-0.90***	**0.78*****
	12	3	27	5	**32**	1.70***	-1.18**	**1.25*****
		6	24	5	**29**	1.70***	-0.99***	**1.24*****
		9	21	5	**26**	1.54***	-1.03***	**1.05*****
		12	18	5	**23**	1.34***	-0.90***	**0.85*****

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 6: Contrarian (Weekly) Returns Part 1/2

The first panel contains the average results across all assets; the following five panels contain the results at the asset level. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Lookback (Months)	Holding (Months)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All	8	8	431	605	**1036**	0.57***	-1.62***	**-0.71*****
		12	411	605	**1016**	0.82***	-1.41***	**-0.51*****
		16	396	600	**996**	0.98***	-1.32***	**-0.41*****
	12	8	396	620	**1016**	0.67***	-1.48***	**-0.64*****
		12	377	619	**996**	0.90***	-1.30***	**-0.47*****
		16	375	601	**976**	1.02***	-1.19***	**-0.34*****
	16	8	339	654	**993**	0.93***	-1.25***	**-0.51*****
		12	334	639	**973**	1.12***	-1.04***	**-0.30*****
		16	334	619	**953**	1.07***	-1.05***	**-0.30*****
BTC	8	8	85	159	**244**	0.00	-1.44***	**-0.94*****
		12	81	159	**240**	0.19	-1.31***	**-0.80*****
		16	77	159	**236**	0.27	-1.22***	**-0.73*****
	12	8	85	155	**240**	0.22	-1.32***	**-0.77*****
		12	81	155	**236**	0.22	-1.22***	**-0.73*****
		16	79	153	**232**	0.18	-1.13***	**-0.68*****
	16	8	66	170	**236**	0.16	-1.13***	**-0.7*****
		12	64	168	**232**	0.11	-0.99***	**-0.69*****
		16	64	164	**228**	0.02	-0.99***	**-0.71*****
LTC	8	8	126	118	**244**	0.45	-1.32***	**-0.41**
		12	122	118	**240**	0.64*	-1.17***	**-0.25**
		16	118	118	**236**	0.62**	-1.21***	**-0.30**
	12	8	122	118	**240**	0.76*	-1.07***	**-0.14**
		12	118	118	**236**	0.75**	-1.06***	**-0.16**
		16	118	114	**232**	0.50*	-1.12***	**-0.29**
	16	8	100	133	**233**	0.46	-1.26***	**-0.52***
		12	99	130	**229**	0.24	-1.12***	**-0.53****
		16	99	126	**225**	0.09	-1.13***	**-0.59*****

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 6: Contrarian (Weekly) Returns Part 2/2

Asset	Lookback (Weeks)	Holding (Weeks)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
XRP	8	8	123	112	**235**	0.86**	-1.18**	**-0.11**
		12	119	112	**231**	1.21***	-0.60	**0.33**
		16	117	110	**227**	1.47***	-0.32	**0.61****
	12	8	105	126	**231**	0.81*	-0.94*	**-0.14**
		12	102	125	**227**	1.31***	-0.47	**0.33**
		16	102	121	**223**	1.84***	-0.07	**0.81*****
	16	8	102	125	**227**	1.47***	-0.21	**0.54**
		12	102	121	**223**	2.08***	0.27	**1.10*****
		16	102	117	**219**	2.03***	0.16	**1.03*****
ETH	8	8	38	92	**130**	1.76***	-3.08***	**-1.67*****
		12	34	92	**126**	2.41***	-2.85***	**-1.43*****
		16	33	89	**122**	3.06***	-2.73***	**-1.16*****
	12	8	32	94	**126**	1.64***	-3.08***	**-1.88*****
		12	28	94	**122**	3.02***	-2.65***	**-1.35*****
		16	28	90	**118**	3.79***	-2.40***	**-0.93****
	16	8	30	92	**122**	3.39***	-2.53***	**-1.08****
		12	29	89	**118**	4.28***	-2.09***	**-0.53**
		16	29	85	**114**	4.52***	-1.88***	**-0.25**
CRIX	8	8	59	124	**183**	0.33	-1.45***	**-0.88*****
		12	55	124	**179**	0.35**	-1.44***	**-0.89*****
		16	51	124	**175**	0.44**	-1.44***	**-0.89*****
	12	8	52	127	**179**	0.35	-1.42***	**-0.91*****
		12	48	127	**175**	0.33*	-1.46***	**-0.97*****
		16	48	123	**171**	0.32**	-1.55***	**-1.03*****
	16	8	41	134	**175**	0.16	-1.47***	**-1.09*****
		12	40	131	**171**	0.23	-1.51***	**-1.10*****
		16	40	127	**167**	0.23	-1.58***	**-1.15*****

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 7: Contrarian (Monthly) Returns Part 1/2

The first panel contains the average results across all assets; the following five panels contain the results at the asset level. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Lookback (Months)	Holding (Months)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All		9	56	114	**170**	0.84***	-1.07***	**-0.44*** **
	9	12	56	99	**155**	0.85***	-1.07***	**-0.38*** **
		18	51	74	**125**	0.33***	0.01	**0.14*** **
		9	50	105	**155**	0.71***	-1.26***	**-0.63*** **
	12	12	50	90	**140**	0.84***	-1.17***	**-0.45*** **
		18	48	62	**110**	0.31***	-0.06**	**0.10** **
		9	44	81	**125**	1.06***	-1.28***	**-0.46*** **
	18	12	44	66	**110**	1.09***	-1.28***	**-0.33** **
		18	40	42	**82**	0.31***	-0.18***	**0.06**
BTC		9	14	29	**43**	0.29	-0.76***	**-0.42*** **
	9	12	14	26	**40**	0.40**	-0.59***	**-0.25* **
		18	14	20	**34**	0.56***	-0.20**	**0.11**
		9	13	27	**40**	0.56***	-0.77***	**-0.34* **
	12	12	13	24	**37**	0.65***	-0.61***	**-0.17**
		18	13	18	**31**	0.69***	-0.23***	**0.16**
		9	10	24	**34**	0.80***	-1.07***	**-0.52*** **
	18	12	10	21	**31**	0.86***	-0.87***	**-0.31* **
		18	10	15	**25**	0.74***	-0.43***	**0.04**
LTC		9	15	28	**43**	0.52*	-0.56	**-0.19**
	9	12	15	25	**40**	0.53**	-0.60*	**-0.18**
		18	14	20	**34**	0.24***	0.17	**0.20*** **
		9	12	28	**40**	0.57**	-0.81**	**-0.40**
	12	12	12	25	**37**	0.56**	-0.89***	**-0.42** **
		18	12	19	**31**	0.32***	0.06	**0.16** **
		9	17	17	**34**	0.59**	-1.63***	**-0.52* **
	18	12	17	14	**31**	0.47***	-1.78***	**-0.55** **
		18	16	9	**25**	0.28***	-0.07***	**0.15*** **

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 7: Contrarian (Monthly) Returns Part 2/2

Asset	Lookback (Months)	Holding (Months)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
XRP		9	20	20	**40**	1.25***	-0.76	**0.24**
	9	12	20	17	**37**	1.24***	-1.05**	**0.19**
		18	17	14	**31**	0.07	0.21**	**0.14*** **
		9	20	17	**37**	0.81*	-1.23**	**-0.13**
	12	12	20	14	**34**	1.13**	-1.28**	**0.14**
		18	18	10	**28**	-0.07	0.09	**-0.02**
		9	15	16	**31**	1.79**	-0.73*	**0.49**
	18	12	15	13	**28**	1.96***	-1.06**	**0.56**
		18	12	10	**22**	-0.03	0.08	**0.02**
ETH		9	1	15	**16**	4.84	-2.32***	**-1.88*** **
	9	12	1	12	**13**	3.61	-2.66***	**-2.18*** **
		18	0	7	**7**		0.25***	**0.25*** **
		9	0	13	**13**		-2.70***	**-2.70*** **
	12	12	0	10	**10**		-2.64***	**-2.64*** **
		18	0	4	**4**		0.21*	**0.21***
		9	0	7	**7**		-1.25*	**-1.25***
	18	12	0	4	**4**		-1.57*	**-1.57***
		18	0	0	**0**			
CRIX		9	6	22	**28**	0.90***	-1.56***	**-1.04*** **
	9	12	6	19	**25**	0.89***	-1.36***	**-0.82*** **
		18	6	13	**19**	0.73***	-0.28***	**0.04**
		9	5	20	**25**	1.02***	-1.63***	**-1.10*** **
	12	12	5	17	**22**	0.89***	-1.43***	**-0.90*** **
		18	5	11	**16**	0.66***	-0.23***	**0.05**
		9	2	17	**19**	0.81*	-1.79***	**-1.51*** **
	18	12	2	14	**16**	1.00***	-1.53***	**-1.21*** **
		18	2	8	**10**	0.42	-0.15***	**-0.04**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 8: Moving Average Crossover Returns Part 1/2

The first panel contains the average results across all assets; the following five panels contain the results at the asset level. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annual returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Strategy	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All	1-5 (0%)	931	932	**1863**	1.10***	0.08	**1.18*** **
	5-20 (0%)	193	188	**381**	1.26***	0.18	**1.45*** **
	1-50 (0%)	204	201	**405**	1.05***	-0.02	**1.02*** **
	1-50 (1%)	123	120	**243**	0.67**	-0.41*	**0.26**
	1-150 (0%)	95	93	**188**	0.83**	-0.07	**0.77** **
	1-150 (1%)	64	67	**131**	0.78**	-0.11	**0.67**
	5-150 (0%)	48	46	**94**	0.82**	-0.06	**0.76* **
	5-150 (1%)	25	16	**41**	0.47	-0.28	**0.19**
	1-200 (0%)	89	87	**176**	0.77*	-0.06	**0.72* **
	1-200 (1%)	54	51	**105**	0.85**	0.02	**0.87** **
	2-200 (0%)	57	55	**112**	0.82**	0.00	**0.81** **
	2-200 (1%)	30	28	**58**	0.64*	-0.19	**0.46**
BTC	1-5 (0%)	211	211	**422**	0.85**	0.01	**0.86* **
	5-20 (0%)	43	42	**85**	0.93*	0.06	**1.00** **
	1-50 (0%)	45	44	**89**	0.77*	-0.12	**0.65**
	1-50 (1%)	25	27	**52**	0.55	-0.35	**0.20**
	1-150 (0%)	13	13	**26**	0.57	0.00	**0.57**
	1-150 (1%)	8	10	**18**	0.66	0.08	**0.73**
	5-150 (0%)	6	6	**12**	0.54	-0.02	**0.52**
	5-150 (1%)	4	3	**7**	0.47	-0.10	**0.38**
	1-200 (0%)	12	12	**24**	0.55	-0.02	**0.53**
	1-200 (1%)	7	7	**14**	0.59	0.02	**0.61**
	2-200 (0%)	7	7	**14**	0.59	0.01	**0.60**
	2-200 (1%)	4	2	**6**	0.46	-0.12	**0.34**
LTC	1-5 (0%)	237	237	**474**	0.51	-0.24	**0.27**
	5-20 (0%)	53	52	**105**	0.84	0.07	**0.91**
	1-50 (0%)	61	61	**122**	0.76	-0.02	**0.75**
	1-50 (1%)	34	32	**66**	0.32	-0.51	**-0.19**
	1-150 (0%)	36	35	**71**	0.79	-0.04	**0.75**
	1-150 (1%)	25	21	**46**	0.56	-0.26	**0.30**
	5-150 (0%)	16	15	**31**	0.85	0.07	**0.92**
	5-150 (1%)	8	4	**12**	0.55	-0.23*	**0.33**
	1-200 (0%)	36	36	**72**	0.50	0.00	**0.50**
	1-200 (1%)	21	19	**40**	0.59	0.09	**0.68**
	2-200 (0%)	23	23	**46**	0.61	0.10	**0.70**
	2-200 (1%)	7	11	**18**	-0.09*	-0.60	**-0.69**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 8: Moving Average Crossover Returns Part 2/2

Asset	Strategy	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
XRP	1-5 (0%)	203	203	**406**	1.62**	0.60*	**2.22*** **
	5-20 (0%)	45	44	**89**	1.41**	0.39	**1.80** **
	1-50 (0%)	49	49	**98**	1.17	0.26	**1.43**
	1-50 (1%)	30	30	**60**	0.17	-0.75	**-0.58**
	1-150 (0%)	27	27	**54**	0.82	0.02	**0.84**
	1-150 (1%)	19	21	**40**	0.89	0.09	**0.98**
	5-150 (0%)	16	16	**32**	0.67	-0.13	**0.55**
	5-150 (1%)	8	8	**16**	0.18	-0.89	**-0.71**
	1-200 (0%)	27	26	**53**	0.77	-0.05	**0.72**
	1-200 (1%)	16	19	**35**	0.92	0.09	**1.01**
	2-200 (0%)	16	15	**31**	0.83	0.00	**0.83**
	2-200 (1%)	13	9	**22**	0.90	0.05	**0.94**
ETH	1-5 (0%)	118	119	**237**	2.22***	0.12	**2.35*** **
	5-20 (0%)	22	21	**43**	2.64**	0.38	**3.01** **
	1-50 (0%)	25	24	**49**	2.08	-0.24	**1.84**
	1-50 (1%)	17	19	**36**	2.09	-0.23	**1.86**
	1-150 (0%)	15	15	**30**	1.19	-0.33***	**0.86**
	1-150 (1%)	8	12	**20**	0.93	-0.56*	**0.38**
	5-150 (0%)	7	7	**14**	1.23	-0.28*	**0.95**
	5-150 (1%)	4	0	**4**	1.51	0.00	**1.51**
	1-200 (0%)	8	8	**16**	1.37	-0.16**	**1.21**
	1-200 (1%)	6	4	**10**	1.42	-0.11	**1.31**
	2-200 (0%)	6	6	**12**	1.38	-0.09	**1.29**
	2-200 (1%)	2	3	**5**	1.39	-0.08	**1.30**
CRIX	1-5 (0%)	162	162	**324**	0.73*	-0.10	**0.63**
	5-20 (0%)	30	29	**59**	1.05**	0.09	**1.13** **
	1-50 (0%)	24	23	**47**	0.86*	-0.10	**0.76**
	1-50 (1%)	17	12	**29**	0.90*	-0.07	**0.83**
	1-150 (0%)	4	3	**7**	0.99	-0.11**	**0.89**
	1-150 (1%)	4	3	**7**	0.99	-0.11**	**0.89**
	5-150 (0%)	3	2	**5**	1.03	-0.05*	**0.98**
	5-150 (1%)	1	1	**2**	-0.02	-0.02	**-0.04** **
	1-200 (0%)	6	5	**11**	0.99	-0.09	**0.90**
	1-200 (1%)	4	2	**6**	1.01	-0.07	**0.93**
	2-200 (0%)	5	4	**9**	0.97	-0.11	**0.86**
	2-200 (1%)	4	3	**7**	0.98	-0.10	**0.87**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 9: Filter Rules Returns Part 1/2

The first panel contains the average results across all assets; the following five panels contain the results at the asset level. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Filter Size (%)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All	0.5	1619	1620	**3239**	0.99***	-0.06	**0.93*** **
	1	1364	1365	**2729**	0.96***	-0.07	**0.89*** **
	2	1035	1038	**2073**	1.07***	0.05	**1.12*** **
	3	814	817	**1631**	1.11***	0.08	**1.18*** **
	4	668	671	**1339**	1.03***	0.00	**1.03*** **
	5	550	553	**1103**	1.14***	0.09	**1.23*** **
	7.5	371	372	**743**	1.25***	0.18	**1.43*** **
	10	282	283	**565**	1.15***	0.07	**1.22*** **
	15	184	183	**367**	1.09***	0.00	**1.09*** **
	20	118	117	**235**	1.14***	0.05	**1.19*** **
BTC	0.5	363	364	**727**	0.63**	-0.20	**0.43**
	1	296	297	**593**	0.68**	-0.14	**0.55**
	2	216	217	**433**	0.74**	-0.09	**0.65**
	3	161	162	**323**	0.91**	0.09	**1.01** **
	4	124	125	**249**	1.01**	0.19	**1.20*** **
	5	99	100	**199**	0.98**	0.16	**1.14** **
	7.5	69	69	**138**	0.91**	0.05	**0.96** **
	10	50	50	**100**	0.91**	0.04	**0.95** **
	15	34	34	**68**	0.73*	-0.14	**0.60**
	20	21	21	**42**	0.80	-0.06	**0.74**
LTC	0.5	411	411	**822**	0.24	-0.51	**-0.27**
	1	343	343	**686**	0.38	-0.37	**0.01**
	2	260	261	**521**	0.58	-0.18	**0.39**
	3	212	213	**425**	0.40	-0.35	**0.05**
	4	177	178	**355**	0.30	-0.46	**-0.16**
	5	148	149	**297**	0.59	-0.18	**0.41**
	7.5	94	94	**188**	0.86	0.07	**0.93**
	10	72	72	**144**	0.73	-0.11	**0.63**
	15	42	42	**84**	0.90	0.08	**0.98**
	20	30	30	**60**	0.82	-0.01	**0.81**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 9: Filter Rules Returns Part 2/2

Asset	Filter Size (%)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
XRP	0.5	361	362	**723**	1.65**	0.68*	**2.32*** **
	1	305	306	**611**	1.55**	0.58*	**2.13*** **
	2	242	243	**485**	1.58**	0.61*	**2.19*** **
	3	195	196	**391**	1.60**	0.63*	**2.24*** **
	4	171	172	**343**	1.26*	0.30	**1.56***
	5	141	142	**283**	1.39**	0.39	**1.78****
	7.5	102	103	**205**	1.39**	0.38	**1.78****
	10	83	84	**167**	1.13*	0.12	**1.26**
	15	54	54	**108**	1.18*	0.13	**1.31***
	20	32	32	**64**	1.42*	0.38	**1.80****
ETH	0.5	226	226	**452**	2.29***	-0.10	**2.19*** **
	1	207	207	**414**	1.98***	-0.25	**1.73****
	2	166	166	**332**	2.10***	-0.13	**1.97****
	3	135	135	**270**	2.07***	-0.16	**1.91****
	4	113	113	**226**	1.96***	-0.27	**1.70****
	5	92	92	**184**	2.18***	-0.05	**2.12****
	7.5	61	61	**122**	2.59***	0.36	**2.95*** **
	10	46	46	**92**	2.58***	0.35	**2.93*** **
	15	35	34	**69**	2.01**	-0.28	**1.73***
	20	23	22	**45**	2.08*	-0.20	**1.88**
CRIX	0.5	258	257	**515**	0.64**	-0.18	**0.46**
	1	213	212	**425**	0.57*	-0.25	**0.33**
	2	151	151	**302**	0.78**	-0.06	**0.72**
	3	111	111	**222**	0.95**	0.08	**1.03****
	4	83	83	**166**	1.04**	0.17	**1.22****
	5	70	70	**140**	0.97**	0.10	**1.07****
	7.5	45	45	**90**	1.02**	0.10	**1.12****
	10	31	31	**62**	0.99*	0.06	**1.05***
	15	19	19	**38**	1.02**	0.11	**1.12****
	20	12	12	**24**	0.96*	0.04	**1.00***

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 10: Trading Range Break Returns

The first panel contains the average results across all assets; the following five panels contain the results at the asset level. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. Total trades and average trades per year are reported. The returns reported are average returns following buy signals, sell signals, and average returns per trade. The last column provides total average annual returns for the strategy.

Asset	Strategy	N(Buy)	N(Sell)	Total Trades	Trades per Year	Mean Return (Buy)	Mean Return (Sell)	Mean Return	Annual Returns
All	50-DAY	736	348	**1084**	50	0.13***	-0.01	0.08***	**4.13*****
	50-DAY (1%)	585	264	**849**	40	0.13***	-0.03**	0.08***	**3.13*****
	150-DAY	532	104	**636**	30	0.14***	-0.01	0.12***	**3.48*****
	150-DAY (1%)	424	76	**500**	23	0.15***	-0.03	0.12***	**2.77*****
	200-DAY	456	78	**534**	25	0.13***	-0.02	0.10***	**2.57*****
	200-DAY (1%)	365	59	**424**	20	0.13***	-0.05	0.10***	**2.02*****
BTC	50-DAY	213	51	**264**	53	0.11***	-0.03	0.08***	**4.21*****
	50-DAY (1%)	161	42	**203**	41	0.09***	-0.05*	0.07***	**2.63*****
	150-DAY	143	17	**160**	32	0.13***	-0.01	0.11***	**3.65*****
	150-DAY (1%)	109	12	**121**	24	0.12***	-0.01	0.10***	**2.48*****
	200-DAY	116	12	**128**	26	0.09***	-0.03	0.08***	**1.93*****
	200-DAY (1%)	89	9	**98**	20	0.07***	-0.04	0.06***	**1.20*****
LTC	50-DAY	102	93	**195**	39	0.15***	0.02	0.09***	**3.48*****
	50-DAY (1%)	89	70	**159**	32	0.15***	0.00	0.09***	**2.72*****
	150-DAY	77	32	**109**	22	0.18***	0.07	0.15***	**3.25*****
	150-DAY (1%)	70	23	**93**	19	0.18***	0.03	0.15***	**2.71*****
	200-DAY	58	32	**90**	18	0.15***	0.07	0.12***	**2.17*****
	200-DAY (1%)	53	23	**76**	15	0.14**	0.03	0.11**	**1.63****
XRP	50-DAY	93	132	**225**	47	0.20***	-0.00	0.08***	**3.92*****
	50-DAY (1%)	85	91	**176**	36	0.22***	-0.02	0.10***	**3.45*****
	150-DAY	50	46	**96**	20	0.26***	-0.06**	0.11**	**2.16****
	150-DAY (1%)	47	33	**80**	17	0.28***	-0.08**	0.13**	**2.14****
	200-DAY	47	28	**75**	16	0.27***	-0.11***	0.13**	**2.00****
	200-DAY (1%)	44	22	**66**	14	0.29***	-0.12**	0.15**	**2.05****
ETH	50-DAY	115	38	**153**	54	0.15***	-0.06	0.10***	**5.26*****
	50-DAY (1%)	103	32	**135**	48	0.14***	-0.07	0.09***	**4.25*****
	150-DAY	84	5	**89**	32	0.17***	-0.07	0.16***	**4.95*****
	150-DAY (1%)	76	4	**80**	28	0.17***	-0.10**	0.15***	**4.14*****
	200-DAY	69	5	**74**	26	0.15***	-0.07	0.13***	**3.54*****
	200-DAY (1%)	61	4	**65**	23	0.14***	-0.10**	0.12***	**2.80*****
CRIX	50-DAY	213	34	**247**	64	0.08***	-0.03	0.07***	**4.32*****
	50-DAY (1%)	147	29	**176**	46	0.09***	-0.02	0.07***	**3.08*****
	150-DAY	178	4	**182**	47	0.09***	-0.02	0.09***	**4.15*****
	150-DAY (1%)	122	4	**126**	33	0.10***	-0.02	0.09***	**3.02*****
	200-DAY	166	1	**167**	44	0.09***	-0.08	0.09***	**3.95*****
	200-DAY (1%)	118	1	**119**	31	0.10***	-0.08	0.10***	**2.96*****

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 11: Comparison of Top Results across All Strategies

The average annual returns are reported here for the top 3 performing variations of each overall strategy type.

	Rank		
Strategy	**1**	**2**	**3**
Momentum (Weekly)	2-week / 2-week **1.36*** **	4-week / 2-week **1.05*** **	2-week / 4-week **0.93*** **
Momentum (Monthly)	12-month / 6-month **1.05*** **	6-month / 6-month **0.63*** **	9-month / 6-month **0.62*** **
Contrarian (Weekly)	16-week / 16-week **-0.30*** **	16-week / 12-week **-0.30*** **	12-week / 16-week **-0.34*** **
Contrarian (Monthly)	9-month / 18-month **0.14*** **	12-month / 18-month **0.10** **	18-month / 18-month **0.06**
Moving Average	5-20 (0%) **1.45*** **	1-5 (0%) **1.18*** **	1-50 (0%) **1.02*** **
Filter Rules	7.5% **1.43*** **	5% **1.23*** **	10% **1.22*** **
Trading Range Break	50-Day (0%) **4.13*** **	150-Day (0%) **3.48*** **	50-Day (1%) **3.13*** **

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 12: Top and Median Asset Performances for the Top Strategies

The top and median ranked assets are shown for each of the top performing individual strategies. Sharpe Ratios are reported in parentheses.

Strategy	Top Asset	Median Asset
Momentum: 2-week / 2-week	ETH: 2.76*** (2.02)	XRP: 1.19** (0.78)
Momentum: 12-month / 6-month	ETH: 3.02*** (2.21)	XRP: 0.92* (0.60)
Contrarian: 16-week / 16-week	XRP: 1.03*** (0.68)	LTC: -0.59*** (-0.45)
Contrarian: 9-month / 18-month	ETH: 0.25*** (0.18)	XRP: 0.14*** (0.09)
Moving Average: 5-20 (0%)	ETH: 3.01** (2.20)	CRIX: 1.13** (1.52)
Filter Rules: 7.5%	ETH: 2.95*** (2.16)	CRIX: 1.12** (1.50)
Trading Range Break: 50-Day (0%)	ETH: 5.26*** (3.85)	BTC: 4.21*** (4.93)

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 13: Momentum (Weekly) Returns with 1 per cent Transaction Cost

This table reports average annual returns across all assets when using a 0.25 and a 1 per cent transaction cost per trade. The final column lists the difference in annual returns for each strategy following an increase in the transaction cost per trade.

Asset	Lookback (Weeks)	Holding (Weeks)	Annual Returns (0.25% TC)	Annual Returns (1% TC)	Difference in Annual Returns
All	2	2	**1.36*** **	**0.97*** **	**-0.39**
		4	**0.93*** **	**0.73*** **	**-0.20**
		8	**0.66*** **	**0.57*** **	**-0.10**
	4	2	**1.05*** **	**0.66*** **	**-0.39**
		4	**0.84*** **	**0.65*** **	**-0.20**
		8	**0.65*** **	**0.55*** **	**-0.10**
	8	2	**0.92*** **	**0.53*** **	**-0.39**
		4	**0.92*** **	**0.73*** **	**-0.20**
		8	**0.67*** **	**0.57*** **	**-0.10**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 14: Momentum (Monthly) Returns with 1 per cent Transaction Cost

This table reports average annual returns across all assets when using a 0.25 and a 1 per cent transaction cost per trade. The final column lists the difference in annual returns for each strategy following an increase in the transaction cost per trade.

Asset	Lookback (Months)	Holding (Months)	Annual Returns (0.25% TC)	Annual Returns (1% TC)	Difference in Annual Returns
All	3	3	**0.17**	**0.11**	**-0.06**
		6	**0.50*** **	**0.47*** **	**-0.03**
		9	**0.22* **	**0.20**	**-0.02**
		12	**0.23** **	**0.21* **	**-0.02**
	6	3	**0.39* **	**0.33* **	**-0.06**
		6	**0.63*** **	**0.60*** **	**-0.03**
		9	**0.31** **	**0.29** **	**-0.02**
		12	**0.35*** **	**0.33*** **	**-0.02**
	9	3	**0.39* **	**0.33**	**-0.06**
		6	**0.62*** **	**0.59*** **	**-0.03**
		9	**0.42*** **	**0.40*** **	**-0.02**
		12	**0.36*** **	**0.34*** **	**-0.02**
	12	3	**0.57** **	**0.51** **	**-0.06**
		6	**1.05*** **	**1.02*** **	**-0.03**
		9	**0.59*** **	**0.57*** **	**-0.02**
		12	**0.43*** **	**0.41*** **	**-0.02**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 15: Contrarian (Weekly) Returns with 1 per cent Transaction Cost

This table reports average annual returns across all assets when using a 0.25 and a 1 per cent transaction cost per trade. The final column lists the difference in annual returns for each strategy following an increase in the transaction cost per trade.

Asset	Lookback (Weeks)	Holding (Weeks)	Annual Returns (0.25% TC)	Annual Returns (1% TC)	Difference in Annual Returns
All	8	8	**-0.71*** **	**-0.72*** **	**-0.02**
		12	**-0.51*** **	**-0.52*** **	**-0.01**
		16	**-0.41*** **	**-0.42*** **	**-0.01**
	12	8	**-0.64*** **	**-0.66*** **	**-0.02**
		12	**-0.47*** **	**-0.48*** **	**-0.02**
		16	**-0.34*** **	**-0.35*** **	**-0.01**
	16	8	**-0.51*** **	**-0.54*** **	**-0.03**
		12	**-0.30*** **	**-0.32*** **	**-0.02**
		16	**-0.30*** **	**-0.32*** **	**-0.01**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 16: Contrarian (Monthly) Returns with 1 per cent Transaction Cost

This table reports average annual returns across all assets when using a 0.25 and a 1 per cent transaction cost per trade. The final column lists the difference in annual returns for each strategy following an increase in the transaction cost per trade.

Asset	Lookback (Months)	Holding (Months)	Annual Returns (0.25% TC)	Annual Returns (1% TC)	Difference in Annual Returns
All	9	9	**-0.44*** **	**-0.46*** **	**-0.02**
		12	**-0.38*** **	**-0.40*** **	**-0.02**
		18	**0.14*** **	**0.13*** **	**-0.01**
	12	9	**-0.63*** **	**-0.65*** **	**-0.02**
		12	**-0.45*** **	**-0.47*** **	**-0.02**
		18	**0.10** **	**0.09** **	**-0.01**
	18	9	**-0.46*** **	**-0.48*** **	**-0.02**
		12	**-0.33** **	**-0.35** **	**-0.02**
		18	**0.06**	**0.05**	**-0.01**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 17: Moving Average Crossover Returns with 1 per cent Transaction Cost

This table reports average annual returns across all assets when using a 0.25 and a 1 per cent transaction cost per trade. The final column lists the difference in annual returns for each strategy following an increase in the transaction cost per trade.

Asset	Strategy	Annual Returns (0.25% TC)	Annual Returns (1% TC)	Difference in Annual Returns
All	1-5	**1.18*** **	**-0.12**	**-1.30**
	5-20	**1.45*** **	**1.18*** **	**-0.27**
	1-50	**1.02*** **	**0.74** **	**-0.28**
	1-50 (1%)	**0.26**	**0.13**	**-0.13**
	1-150	**0.77** **	**0.64* **	**-0.13**
	1-150 (1%)	**0.67**	**0.60**	**-0.07**
	5-150	**0.76* **	**0.69* **	**-0.07**
	5-150 (1%)	**0.19**	**0.18**	**-0.02**
	1-200	**0.72* **	**0.60**	**-0.12**
	1-200 (1%)	**0.87** **	**0.81** **	**-0.05**
	2-200	**0.81** **	**0.73* **	**-0.08**
	2-200 (1%)	**0.46**	**0.43**	**-0.03**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 18: Filter Rules Returns with 1 per cent Transaction Cost

This table reports average annual returns across all assets when using a 0.25 and a 1 per cent transaction cost per trade. The final column lists the difference in annual returns for each strategy following an increase in the transaction cost per trade.

Asset	Filter Size (%)	Annual Returns (0.25% TC)	Annual Returns (1% TC)	Difference in Annual Returns
All	0.5	**0.93*** **	**-1.33*** **	**-2.26**
	1	**0.89*** **	**-1.01*** **	**-1.91**
	2	**1.12*** **	**-0.32**	**-1.45**
	3	**1.18*** **	**0.04**	**-1.14**
	4	**1.03*** **	**0.10**	**-0.94**
	5	**1.23*** **	**0.46**	**-0.77**
	7.5	**1.43*** **	**0.91*** **	**-0.52**
	10	**1.22*** **	**0.83*** **	**-0.39**
	15	**1.09*** **	**0.83*** **	**-0.26**
	20	**1.19*** **	**1.02*** **	**-0.16**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 19: Trading Range Break Returns with 1 per cent Transaction Cost

This table reports average returns per trade and average annual returns across all assets when using a 0.25 and a 1 per cent transaction cost per trade. The final column lists the difference in annual returns for each strategy following an increase in the transaction cost per trade.

Asset	Strategy	Trades per Year	Mean Return (0.25% TC)	Mean Return (1% TC)	Annual Returns (0.25% TC)	Annual Returns (1% TC)	Difference in Annual Returns
All	50-DAY	50	0.08***	0.07***	**4.13*** **	**3.34*** **	**-0.79**
	50-DAY (1%)	40	0.08***	0.06***	**3.13*** **	**2.56*** **	**-0.56**
	150-DAY	30	0.12***	0.10***	**3.48*** **	**3.08*** **	**-0.40**
	150-DAY (1%)	23	0.12***	0.10***	**2.77*** **	**2.39*** **	**-0.38**
	200-DAY	25	0.10***	0.09***	**2.57*** **	**2.21*** **	**-0.36**
	200-DAY (1%)	20	0.10***	0.09***	**2.02*** **	**1.74*** **	**-0.27**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 20: Momentum (Weekly) Returns During 2018

Average annual returns are reported for all strategies which were active during 2018. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Lookback (Weeks)	Holding (Weeks)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All		2	44	61	**105**	-0.71	1.91**	**0.81**
	2	4	46	59	**105**	-1.22	0.36	**-0.33**
		8	52	53	**105**	1.56**	1.20***	**1.38*** **
		2	45	60	**105**	-2.44**	0.64	**-0.68**
	4	4	45	60	**105**	-1.28	0.32	**-0.37**
		8	55	50	**105**	0.78	0.52	**0.66**
		2	46	59	**105**	-2.77**	0.35	**-1.02**
	8	4	48	57	**105**	-1.66*	-0.04	**-0.78**
		8	68	37	**105**	0.39	0.27	**0.35**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 21: Momentum (Monthly) Returns During 2018

Average annual returns are reported for all strategies which were active during 2018. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Lookback (Months)	Holding (Months)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All	3	3	28	6	34	0.72	-1.39	**0.35**
		6	32	2	34	2.11***	-4.66**	**1.71*** **
		9	32	2	34	0.83***	0.17	**0.79*** **
		12	27	7	34	0.96***	-3.27***	**0.09**
	6	3	33	1	34	0.71	-5.15	**0.53**
		6	33	1	34	2.20***	-4.44	**2.00*** **
		9	34	0	34	0.77***	0.00	**0.77*** **
		12	29	5	34	1.10***	-3.38***	**0.45**
	9	3	34	0	34	0.84	0.00	**0.84**
		6	34	0	34	2.26***	0.00	**2.26*** **
		9	34	0	34	0.77***	0.00	**0.77*** **
		12	29	5	34	1.09***	-3.46***	**0.42**
	12	3	34	0	34	0.84	0.00	**0.84**
		6	34	0	34	2.26***	0.00	**2.26*** **
		9	34	0	34	0.77***	0.00	**0.77*** **
		12	32	2	34	1.29***	-3.80**	**0.99*** **

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 22: Contrarian (Weekly) Returns During 2018

Average annual returns are reported for all strategies which were active during 2018. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Lookback (Weeks)	Holding (Weeks)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All	8	8	37	68	**105**	-0.27	-0.45	**-0.39**
		12	24	81	**105**	1.64*	-0.46	**0.02**
		16	10	95	**105**	4.36***	-0.99***	**-0.49**
	12	8	22	83	**105**	0.55	-0.10	**0.03**
		12	4	101	**105**	1.94	-0.68*	**-0.58**
		16	6	99	**105**	5.75***	-1.05***	**-0.66** **
	16	8	5	100	**105**	0.76	-0.17	**-0.12**
		12	3	102	**105**	9.85***	-0.46	**-0.17**
		16	9	96	**105**	5.90***	-0.89***	**-0.30**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 23: Contrarian (Monthly) Returns During 2018

Average annual returns are reported for all strategies which were active during 2018. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Lookback (Months)	Holding (Months)	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All	9	9	0	29	**29**	0.00	-0.92***	**-0.92*** **
		12	5	24	**29**	3.45***	-1.33***	**-0.50**
		18	1	28	**29**	-0.03	-0.02	**-0.02**
	12	9	0	29	**29**	0.00	-0.92***	**-0.92*** **
		12	2	27	**29**	3.79**	-1.54***	**-1.17*** **
		18	4	23	**27**	0.03	-0.05	**-0.04**
	18	9	0	29	**29**	0.00	-0.92***	**-0.92*** **
		12	4	23	**27**	3.39***	-1.25***	**-0.56**
		18	4	19	**23**	0.01	-0.10***	**-0.08*** **

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 24: Moving Average Crossover Returns During 2018

Average annual returns are reported for all strategies which were active during 2018. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Strategy	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All	1-5	93	95	**188**	0.27	1.80***	**2.07** **
	5-20	16	13	**29**	1.75	1.35**	**3.10** **
	1-50	23	18	**41**	2.52*	0.58	**3.10** **
	1-50 (1%)	17	16	**33**	2.65*	0.68	**3.33** **
	1-150	14	9	**23**	5.85**	-0.43***	**5.42* **
	1-150 (1%)	10	8	**18**	5.60**	-0.76*	**4.84**
	5-150	9	4	**13**	7.76**	-0.37**	**7.39** **
	5-150 (1%)	7	3	**10**	5.96**	-0.18	**5.78* **
	1-200	22	17	**39**	7.27**	-0.78***	**6.49* **
	1-200 (1%)	18	12	**30**	7.43**	-0.59***	**6.84* **
	2-200	15	10	**25**	7.40**	-0.66***	**6.74* **
	2-200 (1%)	11	8	**19**	5.89*	-2.29	**3.60**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 25: Filter Rules Returns During 2018

Average annual returns are reported for all strategies which were active during 2018. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. The returns reported are average annualised returns following buy signals, sell signals, and finally total average annual returns for the strategy.

Asset	Filter Size	N(Buy)	N(Sell)	N	Annual Returns (Buy)	Annual Returns (Sell)	Annual Returns
All	0.5	173	171	**344**	-0.69	1.07**	**0.37**
	1	160	158	**318**	-0.64	1.12**	**0.48**
	2	134	133	**267**	-0.19	1.57***	**1.39***
	3	113	112	**225**	0.19	1.57***	**1.76***
	4	91	90	**181**	0.17	1.55***	**1.72***
	5	80	79	**159**	0.04	1.41**	**1.44**
	7.5	54	52	**106**	0.14	1.31**	**1.46**
	10	40	39	**79**	0.24	1.43**	**1.67***
	15	23	21	**44**	0.51	1.47**	**1.98****
	20	18	15	**33**	1.71	1.23**	**2.94****

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Table 26: Trading Range Break Returns During 2018

Average annual returns are reported for all strategies which were active during 2018. N(Buy) and N(Sell) are the number of buy and sell signals generated, and N is the total number of signals. Total trades and average trades per year are reported. The returns reported are average returns following buy signals, sell signals, and average returns per trade. The last column provides total average annual returns for the strategy.

Asset	Strategy	N(Buy)	N(Sell)	Total Trades	Trades per Year	Mean Return (Buy)	Mean Return (Sell)	Mean Return	Annual Returns
All	50-DAY	31	55	86	208	-0.06	0.00	-0.02	**-4.53**
	50-DAY (1%)	27	46	73	176	-0.06	-0.02	-0.03	**-5.46**
	150-DAY	22	0	22	53	-0.03	0.00	-0.03	**-1.73**
	150-DAY (1%)	21	0	21	51	-0.03	0.00	-0.03	**-1.44**
	200-DAY	22	0	22	53	-0.03	0.00	-0.03	**-1.73**
	200-DAY (1%)	21	0	21	51	-0.03	0.00	-0.03	**-1.44**

* Significant at the 90% confidence level
** Significant at the 95% confidence level
*** Significant at the 99% confidence level

Figure 1: Performance of Median Strategies over Time

The top performing individual strategy of each overall strategy type has the individual asset returns ranked by average annual return. The cumulative log return of the median asset in each of these rankings in plotted to show the positive performance of all strategies (excluding contrarian).

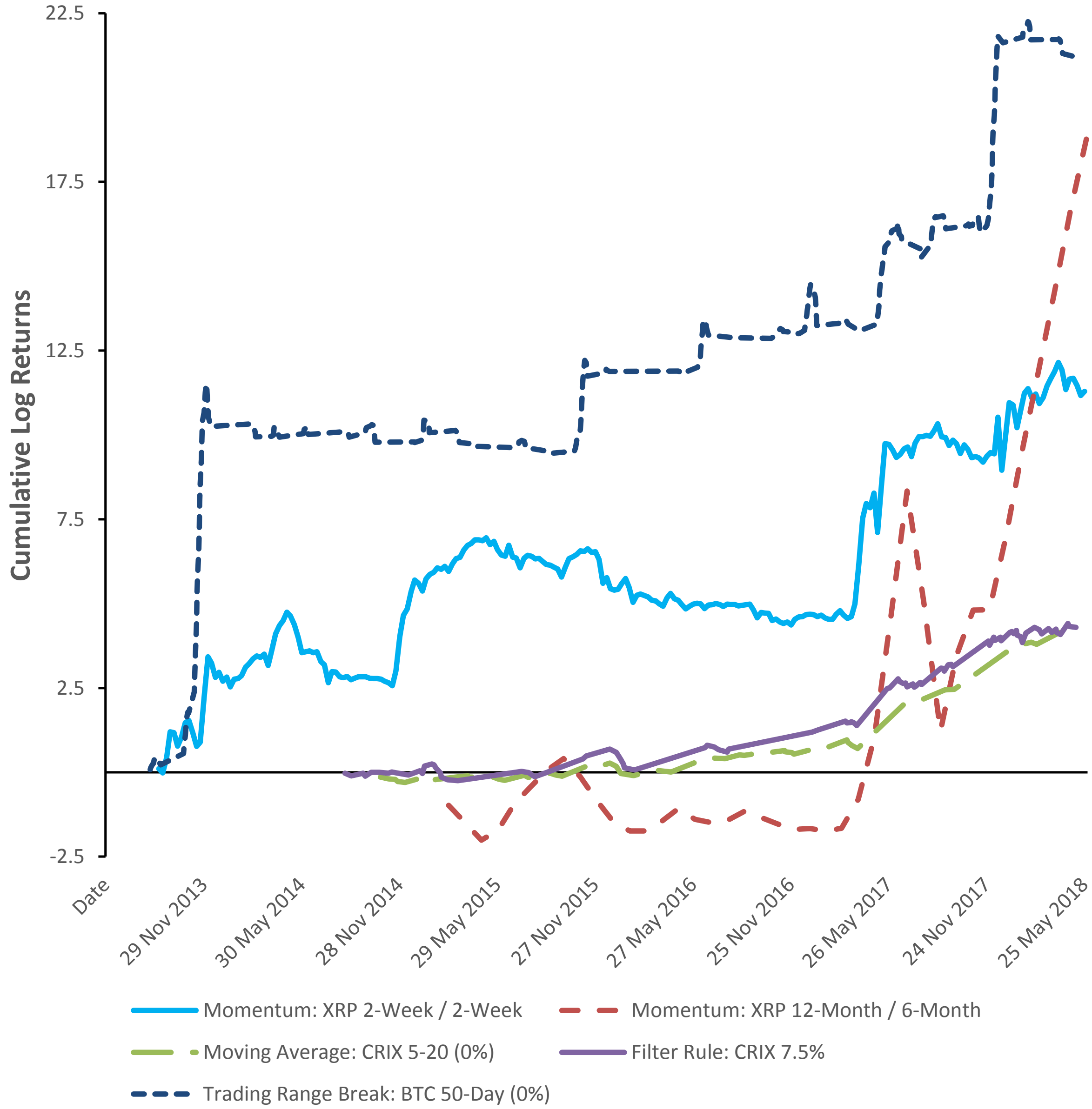


Figure 2: Average Annual Return across All Strategies by Cryptocurrency Asset

Average annual returns across all strategies are plotted for each individual asset to show the difference in their predictability by using technical trading strategies. Assets with a higher average return per strategy show lower levels of weak form market efficiency than assets with a lower average return per strategy.

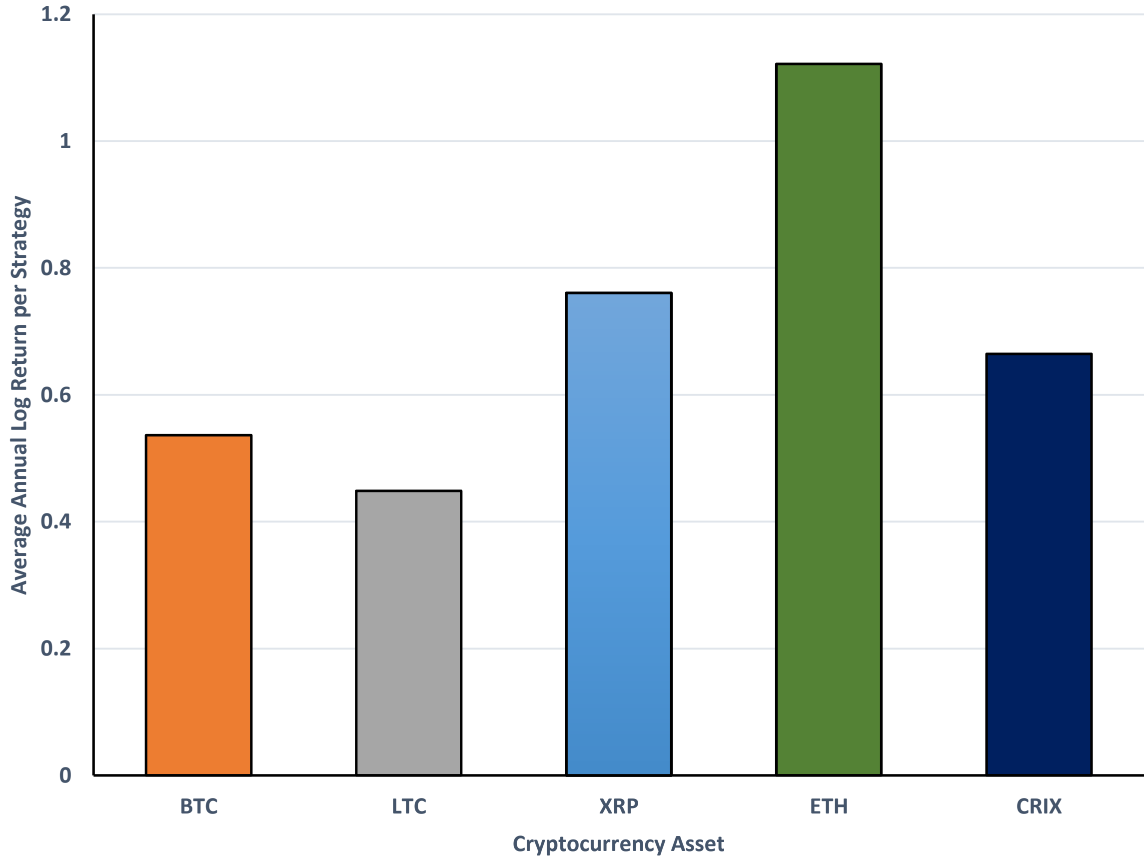
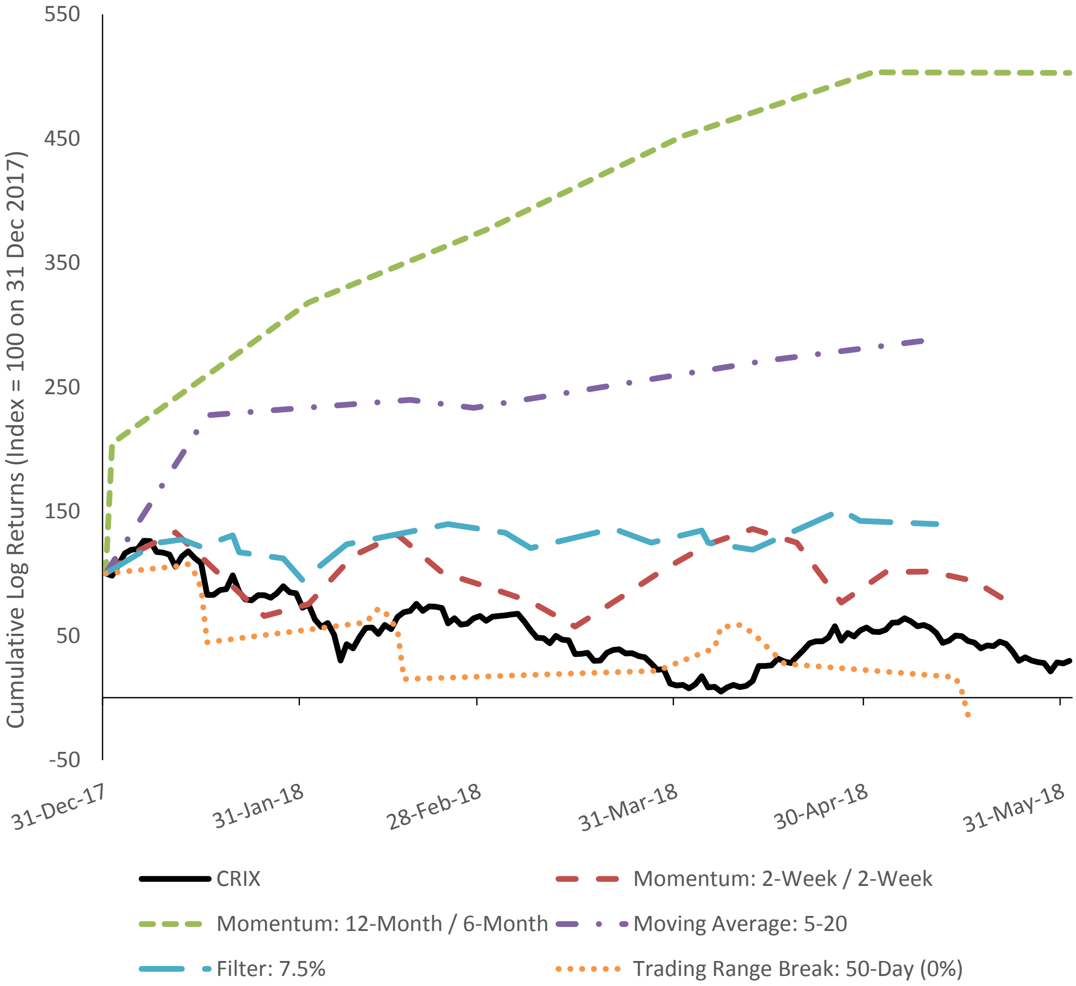


Figure 3: Strategy Returns during 2018 Downturn

Cumulative returns for five strategies (contrarian excluded) are plotted alongside the returns to the CRIX index during 2018. All strategies and the CRIX are indexed to 100 on 31 December 2017. Figure 3 shows the strong performance of four of the five strategies during a downturn period.



8. BIBLIOGRAPHY

Bariviera, A.F., 2017. The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters*, *161*, pp.1-4.

Böhme, R., Christin, N., Edelman, B. and Moore, T., 2015. Bitcoin: Economics, technology, and governance. *Journal of Economic Perspectives*, *29*(2), pp.213-38.

Bondt, W.F. and Thaler, R., 1985. Does the stock market overreact?. *The Journal of finance*, *40*(3), pp.793-805.

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

Caporale, G.M., Gil-Alana, L. and Plastun, A., 2017. Persistence in the Cryptocurrency Market.

Caporale, G.M. and Plastun, O., 2018. Price Overreactions in the Cryptocurrency Market.

CoinMarketCap. 2018a. Top 100 Cryptocurrencies By Market Capitalization. [ONLINE] Available at: https://coinmarketcap.com/. [Accessed 15 June 2018].

Coinmarketcap. 2018b. Total Market Capitalisation. [ONLINE] Available at: https://coinmarketcap.com/charts/. [Accessed 24 June 2018].

Coinschedule. 2018. Cryptocurrency ICO Stats 2018. [ONLINE] Available at: https://www.coinschedule.com/stats.html. [Accessed 24 August 2018].

Conrad, J. and Kaul, G., 1998. An anatomy of trading strategies. *The Review of Financial Studies*, *11*(3), pp.489-519.

Detzel, A.L., Liu, H., Strauss, J., Zhou, G. and Zhu, Y., 2018. Bitcoin: Learning, Predictability and Profitability via Technical Analysis.

Dooley, M.P. and Shafer, J., 1984. Analysis of short-run exchange rate behavior: March 1973 to November 1981. *Floating exchange rates and the state of world trade and payments*, pp.43-70.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), pp.383-417.

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

Forner, C. and Marhuenda, J., 2003. Contrarian and momentum strategies in the Spanish stock market. *European Financial Management*, *9*(1), pp.67-88.

Härdle, W.K. and Trimborn, S., 2015. *Crix or evaluating blockchain based currencies* (No. 2015-048). SFB 649 Discussion Paper.

Hameed, A. and Kusnadi, Y., 2002. Momentum strategies: Evidence from Pacific Basin stock markets. *Journal of financial research*, *25*(3), pp.383-397.

Hudson, R., Dempsey, M. and Keasey, K., 1996. A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices-1935 to 1994. *Journal of Banking & Finance*, *20*(6), pp.1121-1132.

Hurn, S. and Pavlov, V., 2003. Momentum in Australian stock returns. *Australian Journal of Management*, *28*(2), pp.141-155.

James, F.E., 1968. Monthly moving averages—an effective investment tool?. *Journal of financial and quantitative analysis*, *3*(3), pp.315-326.

Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), pp.65-91.

Jegadeesh, N. and Titman, S., 1995. Overreaction, delayed reaction, and contrarian profits. *The Review of Financial Studies*, *8*(4), pp.973-993.

Jegadeesh, N. and Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of finance*, *56*(2), pp.699-720.

Jensen, M. and Bennington, G.A., 1970. Random Walks andTechnical Theories: Some Additional Evidence. *Jour-nal of Finance (May1960)*.

Jiang, Y., Nie, H. and Ruan, W., 2017. Time-varying long-term memory in Bitcoin market. *Finance Research Letters*.

Kość, K., Sakowski, P. and Ślepaczuk, R., 2018. *Momentum and contrarian effects on the cryptocurrency market* (No. 2018-09).

Kristoufek, L., 2018. On Bitcoin markets (in) efficiency and its evolution. *Physica A: Statistical Mechanics and its Applications*, *503*, pp.257-262.

Lakonishok, J., Shleifer, A. and Vishny, R.W., 1994. Contrarian investment, extrapolation, and risk. *The journal of finance*, *49*(5), pp.1541-1578.

Lento, C. and Gradojevic, N., 2007. The profitability of technical trading rules: A combined signal approach. *Journal of Applied Business Research*, *23*(1), p.13.

Levich, R.M. and Thomas, L.R., 1991. *The significance of technical trading-rule profits in the foreign exchange market: a bootstrap approach* (No. w3818). National Bureau of Economic Research.

Malkiel, B.G. and McCue, K., 1985. *A random walk down Wall Street* (Vol. 8). New York: Norton.

Mengoli, S., 2004. On the source of contrarian and momentum strategies in the Italian equity market. *International Review of Financial Analysis*, *13*(3), pp.301-331.

Menkhoff, L., 2010. The use of technical analysis by fund managers: International evidence. *Journal of Banking & Finance*, *34*(11), pp.2573-2586.

Menkhoff*, L. and Schmidt, U., 2005. The use of trading strategies by fund managers: some first survey evidence. *Applied Economics*, *37*(15), pp.1719-1730.

Menkhoff, L. and Taylor, M.P., 2007. The obstinate passion of foreign exchange professionals: technical analysis. *Journal of Economic Literature*, *45*(4), pp.936-972.

Miffre, J. and Rallis, G., 2007. Momentum strategies in commodity futures markets. *Journal of Banking & Finance*, *31*(6), pp.1863-1886.

Moskowitz, T.J., Ooi, Y.H. and Pedersen, L.H., 2012. Time series momentum. *Journal of financial economics*, *104*(2), pp.228-250.

Muga, L. and Santamaria, R., 2007. The momentum effect in Latin American emerging markets. *Emerging Markets Finance and Trade*, *43*(4), pp.24-45.

Nadarajah, S. and Chu, J., 2017. On the inefficiency of Bitcoin. *Economics Letters*, *150*, pp.6-9.

Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system.

Narayanan, A., Bonneau, J., Felten, E., Miller, A. and Goldfeder, S., 2016. *Bitcoin and Cryptocurrency Technologies: A Comprehensive Introduction*. Princeton University Press.

Okunev, J. and White, D., 2003. Do momentum-based strategies still work in foreign currency markets?. *Journal of Financial and Quantitative Analysis*, *38*(2), pp.425-447.

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

Rouwenhorst, K.G., 1998. International momentum strategies. *The Journal of Finance*, *53*(1), pp.267-284.

Schiereck, D., De Bondt, W. and Weber, M., 1999. Contrarian and momentum strategies in Germany. *Financial Analysts Journal*, *55*(6), pp.104-116.

Shen, Q., Szakmary, A.C. and Sharma, S.C., 2007. An examination of momentum strategies in commodity futures markets. *Journal of Futures Markets*, *27*(3), pp.227-256.

Szakmary, A.C., Shen, Q. and Sharma, S.C., 2010. Trend-following trading strategies in commodity futures: A re-examination. *Journal of Banking & Finance*, *34*(2), pp.409-426.

Tiwari, A.K., Jana, R.K., Das, D. and Roubaud, D., 2018. Informational efficiency of Bitcoin—An extension. *Economics Letters*, *163*, pp.106-109.

Urquhart, A., 2016. The inefficiency of Bitcoin. *Economics Letters*, *148*, pp.80-82.

Van Horne, J.C. and Parker, G.G., 1967. The random-walk theory: an empirical test. *Financial Analysts Journal*, *23*(6), pp.87-92.

White, L.H., 2015. The market for cryptocurrencies. *Cato J.*, *35*, p.383.