Research in International Business and Finance 52 (2020) 101176

Contents lists available at ScienceDirect

Research in International Business and Finance

journal homepage: www.elsevier.com/locate/ribaf

High frequency momentum trading with cryptocurrencies

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ARTICLE INFO

Keywords:
Bitcoin
Trading strategies
Momentum strategy
Passive strategy
Exponential moving averages

ABSTRACT

Over the past few years, cryptocurrencies have increasingly been discussed as alternatives to traditional fiat currencies. These digital currencies have garnered significant interest from investment banks and portfolio managers as a potential option to diversify the financial risk from investing in other assets. This interest has also extended to the general public who have seen cryptocurrencies as a way of making a quick profit. This paper provides a first insight into the applicability of high frequency momentum trading strategies for cryptocurrencies. We implemented two variations of a signal-based momentum trading strategy: (i) a time series method; (ii) a cross sectional method. These strategies were tested on a selection of seven of the largest cryptocurrencies ranked by market capitalization. The results show that there exists potential for the momentum strategy to be used successfully for cryptocurrency trading in a high frequency setting. A comparison with a passive portfolio strategy is proposed, which shows abnormal returns when compared with the momentum strategies. Furthermore, the robustness of our results are checked through the application of the momentum strategies other sample periods. We also compare the performances of the signal-based momentum strategies with returns-based versions of the strategies. It is shown that the signal-based strategy outperforms the returns-based strategy. However, there appears to be no single parameterization of the signal-based strategies that can generate the greatest cumulative return over all sample periods.

1. Introduction

In the financial literature, the topic of trading strategies has been reviewed extensively. Some of the most common strategies are the simple price moving average, momentum trading, trading volume, mean reversion, candlestick technical, bootstrap techniques, trading range break, and dynamic volatility trading. Examples that cover these in the literature include (but are not limited to): Kwon and Kish (2002) who tested some of the above models on the New York Stock Exchange (NYSE) index; Serban (2010) who applied a selection of these models to foreign exchange markets; Brock et al. (1992) who applied some of these strategies to the Dow Jones Index; Grinblatt et al. (1995) who tested the momentum trading strategy on mutual funds; Lee and Swaminathan (2000) who applied these trading strategies to stock returns; Guo (2000) who applied some of these strategies to currency options; Marshall et al. (2006) who applied them to the Dow Jones Industrial Average (DJIA) stocks; Murphy (1991) who proposed these as strategies for global stock, bond, commodity and currency markets; Harris and Yilmaz (2009) who implemented a momentum trading strategy for the spot exchange rate.

More recently, Kampouridis and Otero (2017) proposed a new trading strategy using directional changes in maximising

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https://doi.org/10.1016/j.ribaf.2019.101176
Received 15 July 2019; Received in revised form 17 December 2019; Accepted 24 December 2019
Available online 30 December 2019
0275-5319/

profitability in foreign exchange markets; Chang and Lee (2017) incorporated Markov decision processes in a genetic algorithm to formulate trading strategies for stock markets; Liu et al. (2017) introduced an intra-day trading strategy using a 'doubly mean-reverting' process based on conditional modelling of model spreads between pairs of stocks; Xiao and Chen (2018) provided a comparison between reinforcement learning (Q-learning) and machine learning trading strategies for stock returns; Cartea and Jaimungal (2015) proposed a risk metrics approach and fine tuning of high frequency trading strategies. Moskowitza et al. (2012) defined a diversified portfolio of time series momentum strategies and found that time series momentum strategies have the best performance during extreme markets. In Jegadeesh and Titman (1993), the cross-sectional momentum trading was first introduced, and they found that the profitability of these strategies are not due to their systematic risk or to delayed stock price reactions due to common factors.

Cryptocurrencies, such as the ever popular Bitcoin, can be defined as 'currencies' which are built upon blockchain technology and have a cryptographic backbone. They possess a "mathematical protocol" (Narayanan et al., 2016) which determines how the currency is created and ensures security, whilst keeping the rules of the cryptocurrency within the system. A key attraction of cryptocurrencies over traditional fiat currencies like the US Dollar (USD) or British Pound (GBP) are their decentralized nature, meaning that there is no central governing body which oversees the network. Cryptocurrencies have two main features, which are cryptographic hashes and digital signatures. Whilst not all cryptocurrencies were created with the same purpose and intentions, for example Bitcoin as a practical payment method and Ether as a fuel for running applications on the Ethereum network, an area in which they have all thrived in is financial trading. Due to the global availability of exchanges supporting the buying and selling of cryptocurrencies, there has been a surge in public interest and investment. Many now view cryptocurrencies as a way to invest in new technology whilst also making significant profits.

Although cryptocurrencies can be considered to be relatively new, there is already an extensive literature covering them from many different angles. In particular, many researchers have investigated the links between cryptocurrencies, financial markets, and trading and investment. Cocco et al. (2017) analyzed the cryptocurrency market by creating an artificial financial market where heterogeneous agents trade Bitcoins, randomly and speculatively. By simulating the real Bitcoin market, the authors replicated and proved some of the statistical properties of the real Bitcoin market, such as the autocorrelation of absolute returns and the respective cumulative distribution function. Gangwal (2016) analyzed the impact of Bitcoin on an international investor's portfolio – which includes assets such as stocks, bonds, gold, real estate and crude oil. Using data from July 2010 to August 2016, Gangwal (2016) showed that diversifying portfolios with Bitcoin (over the examined period) generates a higher Sharpe ratio and reduces volatility. Optimal portfolios, which include Bitcoin, are then created to show this effect in detail. Eross et al. (2019) analyzed the intraday stylized facts of Bitcoin and found that Bitcoin returns have increased over a 4 year window, however trading volume, volatility and liquidity varied substantially over time. These results also showed similarities with currency markets. Furthermore, Zhang et al. (2019a), analyzed the stylized facts of the four most popular cryptocurrencies ranked according to their market capitalisation. The analysis was conducted on high frequency returns data with varying lags. In addition to using the Hurst exponent, the analysis also considered features of dependence between different cryptocurrencies. Zhang et al. (2019b) performed an analysis of the long term memory effect for the returns of the Ether cryptocurrency. Risk measures such as Value at Risk and Expected Shortfall based on historical Ether data showed higher volatility compared to other financial instruments, and backtesting was also performed to test the extreme tails.

More specifically, with regards to the trading and prediction of future values and prices, in Madan et al. (2015), Bitcoin trading with machine learning (ML) algorithms are explored by using five years' worth of data on 25 features relating to Bitcoin prices and its network. The authors used six different algorithms and showed that they were able to predict whether the price would go up or down the next day with almost 99% accuracy. In addition, they were able to predict the sign of a future price change using 10 min intervals with 50–55% accuracy, by using a combination of binomial classification, random forests, and generalized linear models. Multi-dimensional analysis and impulse analysis are used in Garcia and Schweitzer (2015) to analyze trading strategies for Bitcoin. The results reveal temporal patterns in the Bitcoin network, and a relationship between Bitcoin returns and emotional valence and opinion polarization from Twitter posts. The authors were able to achieve significant profits when incorporating these factors into a trading strategy.

The application of the equal weighted diversification strategy to cryptocurrencies was explored in Rantanen (2015), and the expected return based on the strategy was derived. Results show that compared to a standard investment in Bitcoin, the equal weighted strategy produced a higher mean return and Sharpe ratio even in the presence of increased volatility. Rohrbach et al. (2017) gives a detailed review of the classic momentum trading strategy, explaining both the background and motivation behind each step. The authors tested the strategy on G10 currencies, emerging market currencies, and also cryptocurrencies. They found that the momentum strategy works best for traditional fiat currencies under a time series framework, whereas they work best for cryptocurrencies under a cross sectional framework. In addition, results indicate that the more volatile a currency the higher the Sharpe ratio. Similar to Rohrbach et al. (2017), Hong (2016) also investigated momentum trading strategies with respect to the returns of the Bitcoin/USD exchange rate. Results indicated that Bitcoin returns have strong time series momentum, and that a momentum based trading strategy can generate significant returns and reduce volatility compared with a long only strategy. These momentum based returns are also found to be less correlated with the returns of the S&P 500, and thus Bitcoin could be used to diversify portfolios containing only traditional assets.

Colianni et al. (2015) used supervised machine learning algorithms to predict movements in the cryptocurrency market. Taking Bitcoin as an example, the authors found that the application of techniques such as logistic regression, the Naive Bayes method, and support vector machines, enabled them to predict hourly and daily movements with over 90% accuracy. Kokeš and Bejček (2016) proposed a new Buy–Sell–Transfer (BST) trading strategy for cryptocurrencies, which utilizes the method of short selling and incorporates a modified Floyd–Marshall algorithm. In Chuen et al. (2017), the risk and return characteristics of portfolios of cryptocurrencies were explored via the CRyptocurrency Index (CRIX). Focusing on Bitcoin and other popular 'altcoins', the results showed that incorporating the index into a portfolio of traditional assets can help to diversify and improve its performance. Furthermore, through sentiment analysis, the index is shown to produce a relatively high Sharpe ratio. Khalafi (2013) presented an analysis of algorithmic trading on Bitcoin exchanges, and developed a trading strategy based on spike detection in factors such as Bitcoin transaction volume, Bitcoin transaction traffic, and Bitcoin Wikipedia search volume. Results showed that, using data from 2011–2013, between August 2011 and January 2013 Bitcoin transactions were the only profitable predictor, and between April 2013 and October 2013 Wikipedia search volume was the only profitable predictor.

Jiang and Liang (2017) examines the trading of cryptocurrencies through cryptocurrency portfolio management, by way of neural networks. Training their neural network using data from a year's worth of trading days, the author's backtests over trading periods of 30 minutes were able to generate 10 fold returns within two months. Moreover, the method presented does not require any financial theory and thus can be applied more widely to traditional financial markets.

From the literature, it is evident that the application of financial trading strategies to cryptocurrencies generally involves the use of artificial networks, neural networks, algorithmic trading, trading based on sentiment etc. These are arguably more complex methods which require significant computing power. Our main motivation is to contribute to the literature by examining one of the simplest traditional trading strategies in finance – momentum trading (also known as an active strategy), and investigate whether this strategy can be adapted for use with cryptocurrencies (in high frequency trading) as an alternative to more complex methods, whilst still yielding positive results. The main contributions of this paper are: (i) to investigate whether it is possible to adapt the momentum trading strategy to higher frequency financial data and still achieve positive results; (ii) to compute a passive strategy portfolio and provide a comparison between the passive and active portfolios; (iii) to perform robustness checks by implementing and applying our strategies to in and out of sample periods covering various market states.

The contents of this paper are organized as follows. Section 2 describes the data used in our analysis. In Section 3, we detail the trading strategy and the method of implementation. Section 4 outlines the results, robustness checks, and provides a discussion of these results. Section 5 provides a conclusion and summary of our results.

2. Data

For our analysis, the data consists of the hourly prices of cryptocurrencies versus the US Dollar over the period of 00:00 on 25th February 2017 to 14:00 on 17th August 2017 inclusive, giving us $T = 4141$ h or data points for each cryptocurrency. In comparison, Rohrbach et al. (2017) used daily data for the period of June 2014 to March 2017 in their analysis. As our focus is on the high frequency cryptocurrency market, we chose to use high frequency hourly cryptocurrency price data that was obtained from CryptoCompare[1] via their official API. At the time of writing, this was the maximum amount of hourly data that was available for download. Since CryptoCompare offers data from multiple exchanges, we chose to use the CCAGG exchange data which gives us the aggregated hourly prices of cryptocurrencies (from multiple exchanges) computed by the CryptoCompare website. We obtained data on the top seven cryptocurrencies (ranked by market capitalization) as of February 2017 – the earliest month that our high frequency hourly data goes back to. These are Bitcoin, Ethereum, Dash, Litecoin, MaidSafeCoin, Monero, and Ripple. For a brief introduction to these cryptocurrencies, we refer the readers to Chan et al. (2017) and Ethereum project (2017). We feel that this set gives an adequate representation of the market demand and popularity for cryptocurrencies, as it covers approximately 90% of the total market capitalisation at the starting date. Dogecoin was initially part of the analysis, however, due to anomalies in the price data and with no accurate method of checking and removing these outliers, it was decided that Ethereum should take its place. Thus, in all of our analysis in Section 3, Dogecoin is not included. We note that although the daily data used in Rohrbach et al. (2017) covers a period of almost three years, their analysis misses a key period towards the end of 2017 and beginning of 2018 where there was an exponential rise and fall in the prices of all cryptocurrencies. Our data covers the significantly bullish period in the cryptocurrency market (upturn) in 2017, in our main analysis, but we also extend this to the significantly bearish period (downturn) at the end of 2017/ beginning of 2018 in our robustness check in Section 4.1.

We first provide an analysis of the summary statistics of the hourly exchange rates for the seven cryptocurrencies chosen, which are given in Table 1. The smallest values for the minimum, first quartile, median, mean, third quartile, and maximum are given by Ripple; the largest values for the minimum, first quartile, median, mean, third quartile, and maximum are given by Bitcoin. Arguably, these values and those across the other cryptocurrencies in the set reflect the popularity and monetary value, with larger values indicating a more popular or valuable cryptocurrency. It can be seen that only the skewness of Litecoin is negative, whilst all other cryptocurrencies give a positive value. In terms of the kurtosis, we find that all cryptocurrencies give a negative value indicating that the raw hourly exchange rates in all seven cases possess light tails. The standard deviations and variances for the majority of the cryptocurrencies are significantly large with the exceptions of MaidSafeCoin and Ripple, which give the smallest values. On the other hand, the largest values correspond to Bitcoin and Ethereum, respectively, the two most popular and valuable cryptocurrencies.

As an aside, we briefly examine the indexed hourly exchange rates of the cryptocurrencies in Fig. 1. In our main analysis, indexed prices are introduced and used where the first observation or exchange rate value for each cryptocurrency at 00:00 on 25th February 2017 is normalized to a value of one, and all other prices are normalized relative to this value. This normalisation allows us to see the true variations in the exchange rates of the cryptocurrencies (independent of the monetary values), and allows us to make

[1] CryptoCompare (2017). CryptoComapre API. Available at: https://www.cryptocompare.com/api/.

Table 1
Summary statistics of the hourly exchange rates of Bitcoin, Ethereum, Dash, Litecoin, MaidSafeCoin,Monero and Ripple (versus the US Dollar) from 00:00 on 25th February 2017 to 14:00 on 17th August 2017, inclusive.

Statistic	Bitcoin	Ethereum	Dash	Litecoin	MaidSafeCoin	Monero	Ripple
Minimum	894.21	13.05	23.36	3.76	0.46	11.61	0.01
Q1	1223.04	48.67	76.62	10.27	0.63	20.82	0.03
Median	2010.36	145.47	105.40	27.30	1.03	32.06	0.17
Mean	2006.41	154.04	123.07	25.79	1.03	33.05	0.14
Q3	2600.19	247.44	177.94	42.15	1.33	44.55	0.25
Maximum	4468.02	396.88	247.59	54.74	2.29	59.79	0.40
Skewness	0.53	0.32	0.11	−0.04	0.53	0.05	0.05
Kurtosis	−0.41	−1.31	−1.37	−1.48	−0.41	−1.42	−1.43
SD	801.50	110.31	53.44	16.08	0.41	13.06	0.11
Variance	642400.30	12167.74	2855.78	258.41	0.17	170.46	0.01
CV	39.95	71.61	43.42	62.34	39.95	39.51	75.96
Range	3573.81	383.83	224.23	50.98	1.83	48.18	0.39
IQR	1377.15	198.77	101.32	31.88	0.70	23.73	0.21

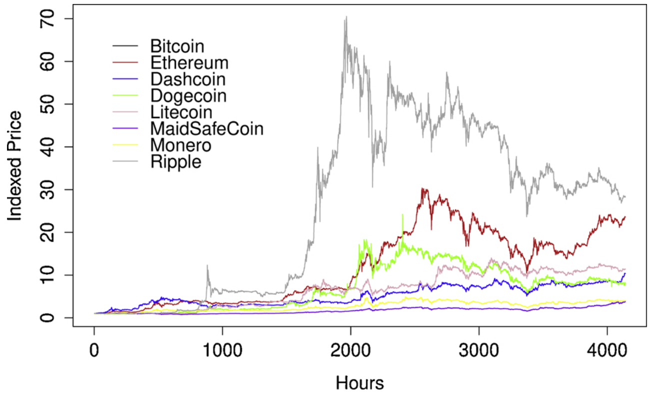

Fig. 1. Indexed prices of the cryptocurrencies from 00:00 on 25th February 2017 to 14:00 on 17th August 2017 (measured in hours since the start time).

comparisons based purely on these variations. We can see that over the whole period analyzed, all cryptocurrencies show a general increase in value of the exchange rate. An interesting trend is that the variations in the exchange rates of both Bitcoin and MaidSafeCoin appear to follow a very similar pattern (the purple and black lines overlap almost identically in Fig. 1). The largest variations and increases in the indexed prices are seen with Ripple and Ethereum, whilst the smallest variations and increases are given by Bitcoin, MaidSafeCoin, and Monero. These trends are reflected in the values of the coefficient of variation, in Table 1, where Ripple and Ethereum give the largest values, and Bitcoin, MaidSafeCoin, and Monero give the smallest values. We note that the results seen here are different to those found in Fig. 26 in Rohrbach et al. (2017). However, this could be explained by the fact that our data is of a higher frequency, and covers a shorter and different time period compared with Rohrbach et al. (2017).

Table 2
Summary statistics of the log returns of the hourly indexed exchange rates of Bitcoin, Ethereum, Dash, Litecoin, MaidSafeCoin, Monero and Ripple (versus the US Dollar) from 00:00 on 25th February 2017 to 14:00 on 17th August 2017, inclusive.

Statistics	Bitcoin	Ethereum	Dash	Litecoin	MaidSafeCoin	Monero	Ripple
Minimum	−0.1446	−0.1864	−0.1417	−0.1075	−0.1445	−0.2369	−0.2907
Q1	−0.0032	−0.0058	−0.0074	−0.0062	−0.0031	−0.0075	−0.0083
Median	0.0005	0.0004	0.0002	0.0000	0.0000	0.0002	0.0000
Mean	0.0003	0.0008	0.0006	0.0006	0.0003	0.0003	0.0008
Q3	0.0045	0.0073	0.0080	0.0069	0.0057	0.0082	0.0089
Maximum	0.0565	0.1325	0.1602	0.1542	0.0566	0.1364	0.3556
Skewness	−1.4295	−0.3586	0.3094	0.6275	−1.3492	−0.5523	0.8556
Kurtosis	19.7142	12.8654	9.3035	8.2259	17.6460	14.0782	29.2903
SD	0.0094	0.0171	0.0183	0.0163	0.0097	0.0179	0.0263
Variance	0.0000	0.0003	0.0003	0.0003	0.0000	0.0003	0.0007
CV	2927.2550	2241.7580	3247.6580	2769.4580	3014.6370	5290.1250	3258.1940
Range	0.2011	0.3189	0.3019	0.2617	0.2010	0.3733	0.6463
IQR	0.0078	0.0131	0.0153	0.0132	0.0088	0.0157	0.0172

After analysing the summary statistics of the raw hourly exchange rates, Table 2 presents those of the log returns of the hourly indexed exchange rates. The log returns of the indexed exchange rates are computed as the indexed rates are used in our main analysis, and the normalisation does not influence the summary statistics. The results show some significant differences from those found in Table 1. Ripple has the smallest minimum and largest maximum, whilst Litecoin has the largest minimum and Bitcoin the smallest maximum. Across all seven cryptocurrencies we find that the mean and median values are all very small and close to zero. In terms of the skewness, only Dash and Litecoin show positive skewness with all others showing negative skewness. The kurtosis values for all seven cryptocurrencies are now positive for the log returns, indicating that they all exhibit greater peakedness and heavier tails than the normal distribution. With respect to the variation in the log returns, Ripple produces the largest standard deviation and variance, with Bitcoin giving the smallest of both values.

3. Method

In this section, we present the basic method for computing the trading strategy. For further details, discussion, and a deeper explanation of the method, we refer readers to Rohrbach et al. (2017) and Baz et al. (2015). Note that the method and naming conventions of the variables used are mostly the same as in Rohrbach et al. (2017). An active portfolio is defined as a trading strategy that aims to outperform the market compared with a specific benchmark. Such methods, discussed in the following, adopt a rolling window approach where in each time period the newest data are incorporated into the strategy and the oldest data are omitted. Hence, the momentum trading strategy is the active portfolio that we propose in this paper. The foundations of the momentum trading strategy revolve around the idea of exponential moving averages (EMA), which can be computed as

$$\mathrm{EMA}_t(P,\alpha) = \begin{cases} P_0, & t = 0 \\ \alpha \cdot P_t + (1-\alpha)\cdot \mathrm{EMA}_{t-1}(P,\alpha), & t > 0 \end{cases}, \tag{1}$$

where $P_0 = 1$, P_t is the indexed exchange rate of a cryptocurrency at time t, and $\alpha = \frac{1}{n_k}$ is the constant weighting factor.

The influence of older values in the EMA is determined by α, and thus n_k, and we follow the method as described in Rohrbach et al. (2017) and Baz et al. (2015), by selecting three arbitrary time periods and letting n_k take a range of different values in order to obtain 'short' and 'long' EMAs. For both cases, we select three n_k values of $n_{k,s} = (8, 16, 32)$ and $n_{k,l} = (24, 48, 96)$, where n_k denotes the kth value, $k = 1, 2, 3$ corresponding to the short (s) and long (l) EMAs, respectively. Although these exact values of $n_{k,s}$ and $n_{k,l}$ were proposed for use with daily data in both Baz et al. (2015) and Rohrbach et al. (2017), we adopt them for use with higher frequency hourly data and believe that they are satisfactory. Note that with this method of computing the EMAs, there is no specific criteria for selecting the values of both $n_{k,s}$ and $n_{k,l}$, thus, these can take any value that one wishes.

Given that the weighting factor in the moving average decreases exponentially, meaning that the influence of past data also decreases in the same manner, we feel that this is particularly suited to our higher frequency hourly data. It can often be seen that the exchange rates of cryptocurrencies show short bursts of upwards or downwards movements over the course of a few hours, and an EMA can capture this shorter term influence. With the momentum trading strategy, the use of EMAs and their crossover points can help to determine when the momentum or general trend of prices may change. As EMAs reflect the general trend of the data, it can be shown (by graphing a short and long EMA on a single plot) that when a shorter EMA crosses over a longer EMA this indicates a bullish signal (a change towards a positive trend), and when a shorter EMA crosses below a longer EMA this indicates a bearish signal (a change towards a negative trend).

Of course, one would like these crossover points to coincide with or be as close as possible to the points at which the true data changes significantly from a positive to a negative trend (and vice versa). However, there will always be a lag between a change in the trend in the real data and the corresponding intersection in a pair of EMAs. The greater the difference between $n_{k,s}$ and $n_{k,l}$, the longer the delay (Rohrbach et al., 2017). We check that the crossover points are relatively close to the points where significant changes in trends occur in the real data, and believe that these are satisfactory for our analysis. As an example, Fig. 2 shows the plot of the indexed price of Bitcoin, a short EMA ($n_{1,s} = 8$), and a long EMA ($n_{1,l} = 24$), for a particular period of 1000 h. Furthermore, whilst our analysis does not focus on it, it could be possible to optimize the parameters of $n_{k,s}$ and $n_{k,l}$ according to the real data, however, we

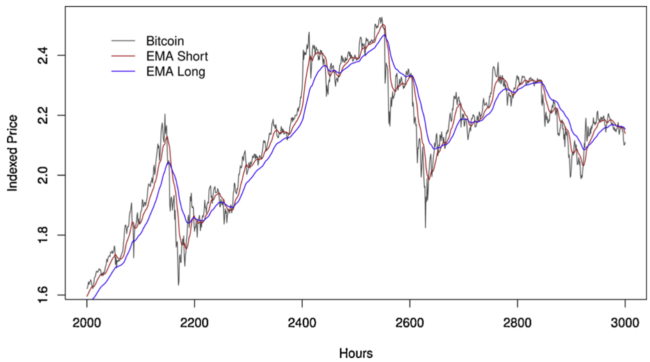

Fig. 2. Plot of the indexed price of Bitcoin, a short EMA ($n_{1,s} = 8$), and a long EMA ($n_{1,l} = 24$), over a particular period of 1000 h.

do not feel it to be necessary in this case.

We compute the EMAs for the indexed prices of the cryptocurrencies, which gives us six sets of EMA values corresponding to the n_k values chosen, for each of the seven cryptocurrencies. We then compute the base signal for the momentum strategy using

$$x_k = \text{EMA}\left(P, \frac{1}{n_{k,s}}\right) - \text{EMA}\left(P, \frac{1}{n_{k,l}}\right), \tag{2}$$

for $k = 1, 2, 3$, as in Rohrbach et al. (2017) and Baz et al. (2015). The values of x_k can either be positive, negative or equal to zero, corresponding to a positive trend, negative trend, or a point where the two EMAs intersect, respectively Rohrbach et al. (2017).

The next step is to normalize the x_k signal values. In the literature, it is commonly found that the signal is transformed by normalising across both a shorter and then a longer time period. For example, in Baz et al. (2015) and Rohrbach et al. (2017) the base signal is first normalized using a three month rolling standard deviation of the respective price or exchange rate, followed by a second normalisation using a one year rolling standard deviation of the normalized signal itself. As noted by Rohrbach et al. (2017), the purpose of this two-step normalisation of the signal values is essentially to equalize the values according to the volatility in the prices. By doing so, the signal is dampened during periods of high volatility, and in the more stable periods the signal is enhanced Rohrbach et al. (2017). For consistency, we also transform our signal twice, however, as our data is hourly instead of daily (as in Baz et al., 2015; Rohrbach et al., 2017) our parameters are not the same. Using three month and one year rolling standard deviations is not appropriate, and thus we suggest using shorter time frames of 12 and 24 h (short) rolling standard deviations, and 168 and 720 h or one week and one month (long) rolling standard deviations. We believe that using rolling standard deviations over shorter time frames will capture the volatility in the exchange rate more effectively, and thus provide a better normalisation.

The first normalisation can be computed as

$$y_k = \frac{x_k}{\widehat{\sigma_{t_1}}(P)}, \tag{3}$$

with $t_1 = 12$ or 24, where x_k is the base signal, and $\widehat{\sigma_{t_1}}(P)$ is the rolling 12 or 24 h standard deviation of the respective indexed exchange rate of a cryptocurrency. For example, in the case of the 12 h rolling standard deviation, for a particular time point t, we can compute the normalisation as

$$\frac{x_{k,t}}{\widehat{\sigma_{12}}(P_t, \ldots, P_{t-11})}.$$

Note that computing this rolling standard deviation leads to a loss of the first 11 or 23 x_k signal values, respectively. Following this, the second normalisation can be computed as

$$z_k = \frac{y_k}{\widehat{\sigma_{t_2}}(y_k)}, \tag{4}$$

with $t_2 = 168$ or 720. Again, due to the method of computing the rolling standard deviations, there is a loss of the first 167 or 719 y_k signal values, respectively. The combinations of these normalisations are summarized in Table 3 along with the total observations lost.

The final step in computing the momentum signal is to scale our normalized signal values z_k, by following the method presented in Rohrbach et al. (2017). Our z_k signals are scaled using the expression (Eq. (8) in Rohrbach et al., 2017)

$$u_k(z_k) = \frac{z_k \cdot e^{-z_k^2/4}}{\sqrt{2} \cdot e^{-1/2}}, \tag{5}$$

and the final momentum signal is calculated by taking the average of all the u_k signals, i.e. $\frac{1}{3}\sum_{k=1}^{3} u_k$.

We note here that expressions (3) and (4) in the normalisation process may prove to be problematic in some situations. The main problem is that x_k could take a value of zero, and we are also dividing by the standard deviation of a set of lagged prices in expression (3), which could also take a value of zero if the set of lagged prices are all identical. In our computations, we accounted for this, by setting the following conditions:

- If $x_k = 0$, then the corresponding y_k and z_k are both equal to zero.
- If $x_k \neq 0$ but $\widehat{\sigma_{t_1}}(P) = 0$, then assume that the corresponding z_k is equal to zero.

Table 3
Combinations of rolling standard deviations used, short and long, and the resulting total number of signal values lost.

Normalisation (short)	Normalisation (long)	Total obs. lost
12 h (half day)	168 h (one week)	178 (11 + 167)
12 h (half day)	720 h (one month)	730 (11 + 719)
24 h (one day)	168 h (one week)	190 (23 + 167)
24 h (one day)	720 h (one month)	742 (23 + 719)

- If $x_k \neq 0$ and $\widehat{\sigma_{t_1}}(P) \neq 0$, but $\widehat{\sigma_{t_2}}(y_k) = 0$, in the corresponding z_k, then assume that the corresponding z_k is equal to zero.

We also compared the resulting hourly and cumulative returns under these conditions with those under other parameter conditions, however, the differences appeared to be negligible.

As in Baz et al. (2015) and Rohrbach et al. (2017) we consider two portfolio types: time series and cross sectional portfolios, respectively. In both portfolios, every hour the price of the cryptocurrencies is observed and two events occur (in the following order): (i) the portfolio is reset; (ii) an investment is made. Note that it is assumed that in an initial time period of $t = 0$, some investment is made (in line with the conditions described below) such that some returns on the portfolios exist at time $t = 1$, and the portfolios can be reset. When the portfolios are reset at any time t, investments (buys/sells) made at time $t - 1$ are balanced (sold/bought), resulting in a return on the investment.

In the time series portfolio, after the portfolio is reset, an investment is made in all cryptocurrencies according to the corresponding signals divided by the number of cryptocurrencies, in this case, seven. When the price of a cryptocurrency at some time $t - 1$ is observed, the signal is computed and determines the investment in the cryptocurrency to be made at time $t - 1$. If the signal is positive, this indicates that a purchase of $\frac{\text{signal}}{7}$ units of US Dollars of the cryptocurrency should be made; if the signal is negative, this indicates that a sale of $\frac{\text{signal}}{7}$ units of US Dollars of the cryptocurrency should be made. This theoretically generates a return $R_{TS,t}$ in the following time period t (when the portfolio is reset), from this investment at time $t - 1$, for each cryptocurrency, of

$$R_{\text{TS},t} = \text{Signal}_{t-1} \times \frac{1}{7} \times \frac{1}{P_{t-1}} \times R_t, \tag{6}$$

when either $Signal_{t-1} > 0$ or $Signal_{t-1} < 0$, $\frac{1}{P_{t-1}}$ denotes the indexed exchange rate of one US Dollar to the respective cryptocurrency at time $t - 1$, R_t denotes the log one-period returns of the indexed exchange rate of the respective cryptocurrency at time t, and

$$R_{\text{TS},t} = 0, \tag{7}$$

when $Signal_{t-1} = 0$.

In the case of the cross sectional portfolio, after the portfolio is reset we have an investment strategy which differs slightly from the time series case. Here, an investment is instead made only in the top three and bottom three cryptocurrencies, respectively, defined as the three cryptocurrencies with the largest and smallest signals in a given time period. Again, when the prices of each cryptocurrency at some time $t - 1$ are observed the signals are computed, however, the signals are then ranked from largest to smallest. The investment in the cryptocurrencies is as follows, for the top three cryptocurrencies a purchase of $\frac{1}{6}$ units of US Dollars of each cryptocurrency should be made; for the bottom three cryptocurrencies a sale of $\frac{1}{6}$ units of US Dollars of each cryptocurrency should be made. This theoretically generates a return $R_{CS,t}$ in the following time period t (when the portfolio is reset), from this investment at time $t - 1$, of

$$R_{\text{CS}_{\text{high}},t} = \frac{1}{6} \times \frac{1}{P_{t-1}} \times R_t, \tag{8}$$

for the three cryptocurrencies with the largest signals, and

$$R_{\text{CS}_{\text{low}},t} = -\frac{1}{6} \times \frac{1}{P_{t-1}} \times R_t, \tag{9}$$

for the three cryptocurrencies with the smallest signals.

Finally, we are able to compute the total hourly returns (on all investments made at $t - 1$) at each time period t, when using the two strategies, by simply summing the returns $R_{TS,t}$ of each cryptocurrrency at time t (time series), or by summing the three high returns $R_{\text{CS}_{\text{high}},t}$ and three low returns $R_{\text{CS}_{\text{low}},t}$ (cross sectional).

For comparison purposes, a passive portfolio is also proposed as an alternative method to the momentum trading strategy (active portfolio), and the results are compared for the high frequency trading of cryptocurrencies. In a passive portfolio, on the one hand, the strategy is built to track a market weighted index, but on the other hand, the strategy is fairly static. Under these circumstances, fixed time periods are more suitable for the strategy (as opposed to the rolling window approach) and in this comparison the passive portfolio was computed using two different methods. One approach varied the weights every month, mirroring the share (percentage) of the live market capitalisation corresponding to a specific cryptocurrency on the first day of every month. The data relating to the market capitalisation of cryptocurrencies was obtained from the CryptoCompare website (see Footnote [1]). The second approach was to implement fixed weights throughout the whole time period considered, with the fixed weights being computed only on the first day that the strategy was implemented. The fixed weights for each cryptocurrency were computed as in the first passive strategy.

4. Results and discussion

We use the momentum trading signal and strategy described in Section 3 and test it on our data of the indexed exchange rates for the seven chosen cryptocurrencies. As mentioned in Section 3, due to the normalisation process, we lose some of our original data and signal values, thus the start time of the analysis varies depending on the combination of rolling standard deviations used. However, the end time of the analysis remains the same for all tests. These details are summarized below in Table 4.

Table 4
Start and end times in the analysis, for all combinations of rolling standard deviations.

Normalisation (short)	Normalisation (long)	Start Time	End time
12 h (half day)	168 h (one week)	10:00 4th March 2017	14:00 17th August 2017
12 h (half day)	720 h (one month)	10:00 27th March 2017	14:00 17th August 2017
24 h (one day)	168 h (one week)	22:00 4th March 2017	14:00 17th August 2017
24 h (one day)	720 h (one month)	22:00 27th March 2017	14:00 17th August 2017

Table 5 shows the correlations between all pairs of the hourly returns of the exchange rates of the seven cryptocurrencies over the time period considered. We find that Ripple appears to be the least correlated with all other cryptocurrencies. Interestingly, and perhaps surprisingly, it can be seen that the returns of MaidSafeCoin are strongly and positively correlated with those of Bitcoin. This is further supported by the fact that the trend of the indexed exchange rates for both cryptocurrencies in Fig. 1 is almost identical too, indicating that the movements in the exchange rates and returns of both are very similar. The second most positively correlated pair are Bitcoin and Ethereum, and this may be expected as they are arguably the two most popular cryptocurrencies at present. Other notable positively correlated pairs are Bitcoin with Litcoin, and Ethereum with MaidSafeCoin and Monero. However, we note that basic correlation-based measures of connectedness are perhaps less useful when it comes to the analysis of financial markets, in part, because they reflect only linear pairwise relationships (Diebold and Yilmaz, 2014). There exist many other methods which can be used to measure the interdependence in financial markets, a particular example being the 'spillover index' proposed in Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), and Diebold and Yilmaz (2014). This measure is based on vector autoregressive models and interdependence is computed as the share of an asset i's forecast error variance that comes from the shock to another asset j, for all $j \neq i$, across all assets $i = 1, \ldots, N$ being analyzed. This method can be used to analyze interdependence across but also within particular markets, and is strongly connected with variance decomposition and network graph connectedness (Diebold and Yilmaz, 2014).

The cumulative and daily returns, respectively, for all possible combinations of rolling standard deviations, generated by the time series and cross sectional strategies are presented and compared in Figs. 3–6. In Fig. 3, using the shortest rolling standard deviations of 12 and 168 h, respectively, it can be seen that the cumulative returns from both the time series and cross sectional strategies are fairly similar in shape. The distribution of the daily returns for each portfolio type are also similar. Although the cross sectional strategy generates some significant negative returns initially, compared with the time series strategy it also generates more positive returns with a larger magnitude early on. The comparison in Fig. 4, using rolling standard deviations of 24 and 168 h, respectively, shows that the cumulative returns for the two variations are similar in shape to those in Fig. 3, and are also similar in levels. Looking at the daily returns, we find a similar trend where the cross sectional strategy experiences larger positive returns in the initial part of the analysis as in Fig. 3.

In Fig. 5, using rolling standard deviations of 12 and 720 h, respectively, we find that the cumulative returns generated by both the time series and cross sectional strategies have a different shape to those in Figs. 3 and 4, with the time series returns being greater than the cross sectional. From the distribution of daily returns, it can be seen that those corresponding to the cross sectional strategy are similar to those in Fig. 4, however, there appear to be more significantly negative returns in the initial part of the analysis in this scenario.

Using the longest rolling standard deviations of 24 and 720 h, respectively, Fig. 6 shows that the cumulative returns generated by the time series strategy form a similar trend to those in Fig. 5. However, those generated by the cross sectional strategy are somewhat different in the initial time periods. The cumulative returns here are similar to those in Fig. 5, with the returns corresponding to the time series strategy still exceeding those of the cross sectional strategy. Turning our attention towards the daily returns, for the time series strategy they are again similar to those in Fig. 5, but for the cross sectional strategy there are less significantly large negative returns at the start of the time period in our analysis.

Combining the plots of the cumulative returns (Fig. 7), provides a clearer comparison between the performance of the time series and cross sectional variations of the strategy across all parameterzations. We note that in Baz et al. (2015) and Rohrbach et al. (2017), the time periods considered in the rolling standard deviations were fixed. When using a long rolling standard deviation over 168 h (one week), it can be seen that the cumulative returns generated by the cross sectional strategy outperform those from the time series

Table 5
Correlations between the hourly returns of the exchange rates of Bitcoin, Ethereum, Dash, Dogecoin,Litecoin, MaidSafeCoin,Monero and Ripple (versus the US Dollar) from 00:00 on 25th February 2017 to 14:00 on 17th August 2017.

Cryptocurrency	Bitcoin	Ethereum	Dash	Litecoin	MaidSafeCoin	Monero	Ripple
Bitcoin	1.0000	0.4235	0.2763	0.3713	0.9741	0.3500	0.2248
Ethereum	0.4235	1.0000	0.2893	0.3181	0.4080	0.3889	0.2063
Dash	0.2763	0.2893	1.0000	0.2277	0.2683	0.2705	0.1462
Litecoin	0.3713	0.3181	0.2277	1.0000	0.3626	0.2737	0.1784
MaidSafeCoin	0.9741	0.4080	0.2683	0.3626	1.0000	0.3384	0.2212
Monero	0.3500	0.3889	0.2705	0.2737	0.3384	1.0000	0.1837
Ripple	0.2248	0.2063	0.1462	0.1784	0.2212	0.1837	1.0000

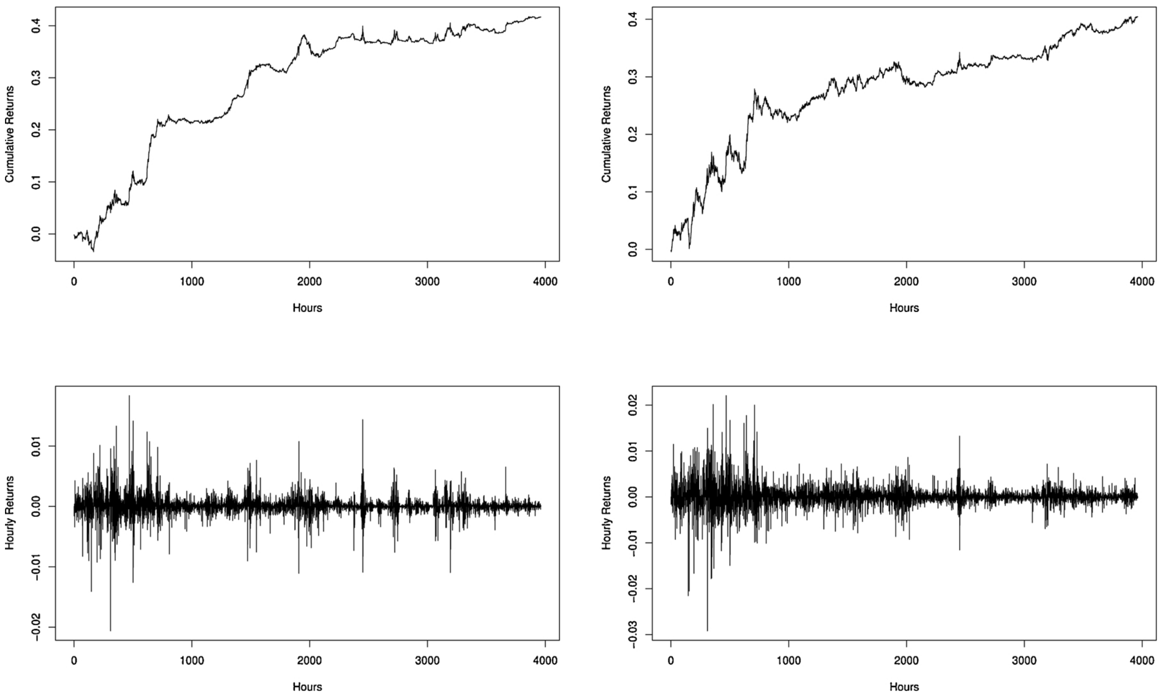

Fig. 3. Cumulative (top) and daily (bottom) returns, using rolling standard deviations of 12 and 168 h, using the time series portfolio method (left) and cross sectional portfolio method (right).

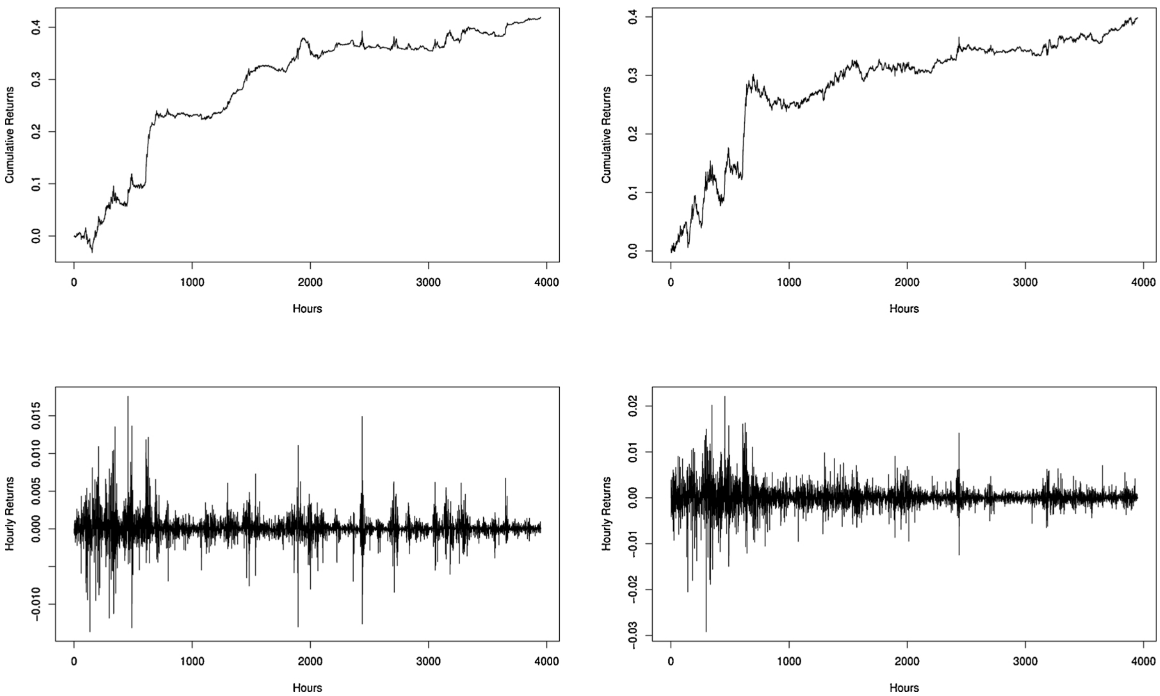

Fig. 4. Cumulative (top) and daily (bottom) returns, using rolling standard deviations of 24 and 168 h, using the time series portfolio method (left) and cross sectional portfolio method (right).

strategy in the initial time period. However, this trend is reversed in the later time periods. In particular, when combined with a short rolling standard deviation over 12 hours, this difference appears to be more pronounced. However, the overall trends of the cumulative returns are similar for both with a short rolling standard deviation of 12 and 24 h. When using a long rolling standard deviation over 720 h (one month), we note that the cumulative returns generated by the time series strategy exceed those from the

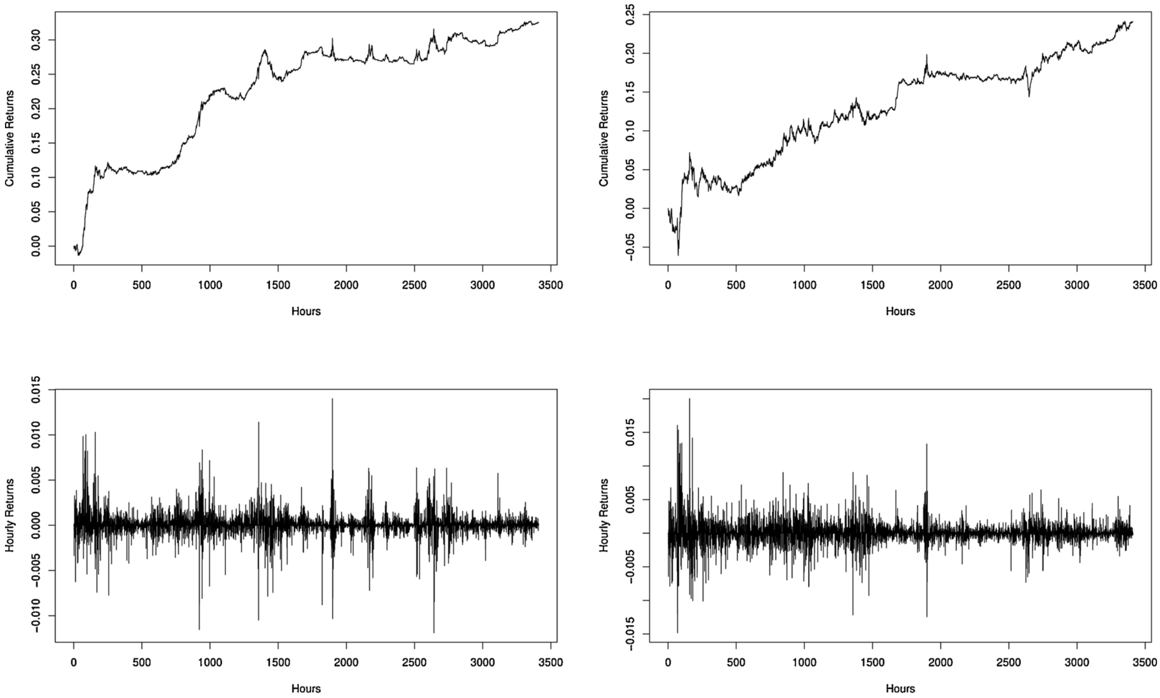

Fig. 5. Cumulative (top) and daily (bottom) returns, using rolling standard deviations of 12 and 720 h, using the time series portfolio method (left) and cross sectional portfolio method (right).

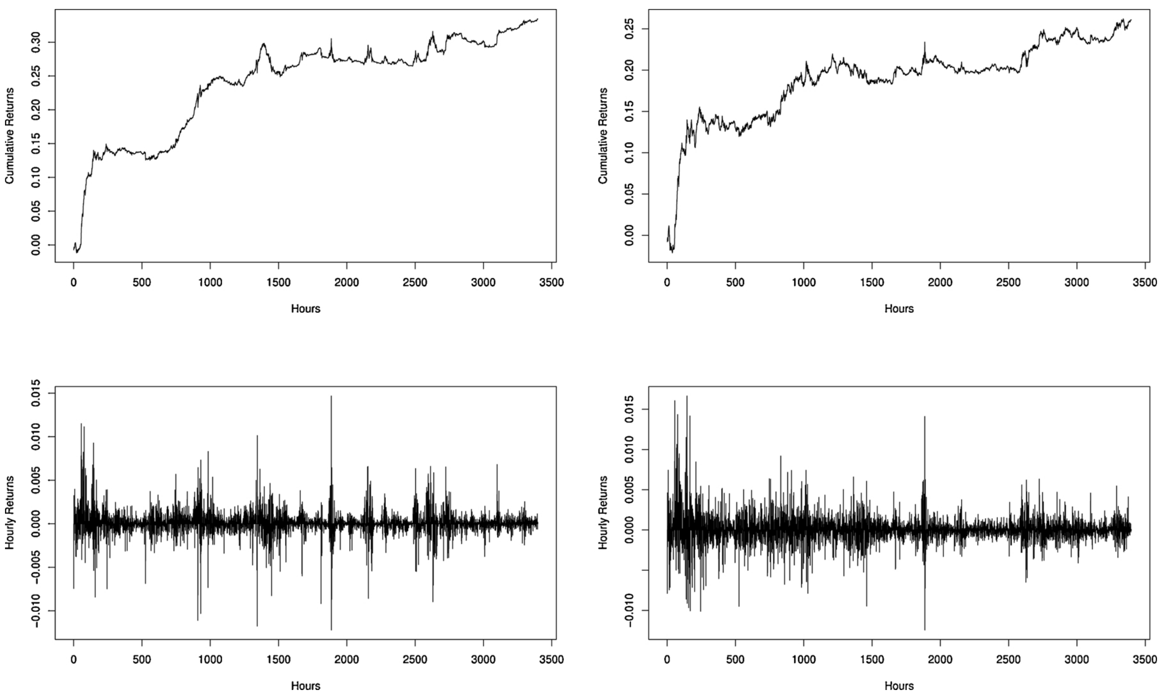

Fig. 6. Cumulative (top) and daily (bottom) returns, using rolling standard deviations of 24 and 720 h, using the time series portfolio method (left) and cross sectional portfolio method (right).

cross sectional strategy. Although the levels of the cumulative returns are smaller than when using a long rolling standard deviation of 168 hours, this difference is significantly greater when combined with a short rolling standard deviation over 12 h as opposed to 24 h.

In general, it appears that using shorter time periods in the rolling standard deviations leads to increased cumulative returns. The

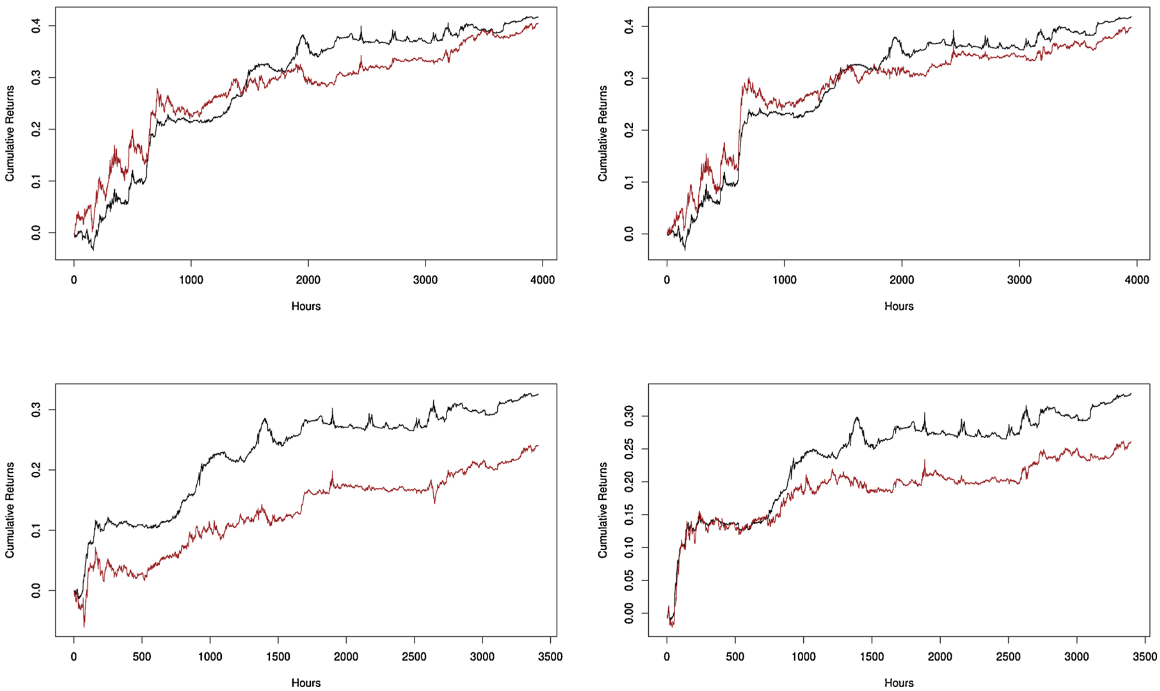

Fig. 7. Comparison of the cumulative returns from the time series portfolio method (black) and cross sectional portfolio method (red) using rolling standard deviations of: 12 and 168 h (top left); 24 and 168 h (top right); 12 and 720 (bottom left); 24 and 720 h (bottom right).

trend of the cumulative returns generated by the time series strategy appears similar in all cases tested, with the only difference being in the magnitudes of the cumulative returns and the magnitudes of the differences between the returns. Those generated by the cross sectional strategy show some differences between long rolling standard deviations over 168 and 720 h, respectively. This may arise from the difference in the ordering of the signals at each time period when 168 and 720 h, respectively, are used. To recap, in the cross sectional variation of the strategy, the top three cryptocurrencies with the largest signals are bought, whereas the bottom three with the smallest signals are sold. This means that at each time period, out of the set of seven cryptocurrencies, one is always omitted in the calculations. Therefore, given that the returns generated by the cross sectional strategy are determined by the ordering of the signals and not the numerical value of the signal, this would seem to suggest that the effect of the cryptocurrencies omitted at each time point when using a long rolling standard deviation of 720 h may have more influence than that when using 168 h.

In Rohrbach et al. (2017), similar methods were tested against daily cryptocurrency data which covered an almost identical set of cryptocurrencies. The results showed in an analysis over an approximate one and a half year period from September 2015 to March 2017, that the time series and cross sectional strategies could generate cumulative returns of approximately 0.9 and 1.2 (in terms of the log returns of indexed daily cryptocurrency exchange rates). Our results presented here extend this analysis to higher frequency hourly cryptocurrency price data, and show that it is possible to adapt the momentum strategy and still achieve positive results. More specifically, our results show that we are able to achieve the highest cumulative returns of approximately 0.4 in less than six months, when using the two strategies. Note here that we do not analyze the effect of drawdowns as in Rohrbach et al. (2017).

Although the results have positive implications on cryptocurrency trading, especially in a high frequency setting, we should note that trading is currently much more limited compared with traditional financial assets and currencies. As noted in Rohrbach et al. (2017), very few exchanges offer the short selling of cryptocurrency-fiat pairs, and it appears that those offering short selling functions only allow it with cryptocurrency pairs. Therefore, in practice, implementing both the time series and cross sectional strategies may not be truly possible until cryptocurrency exchanges fully support the short selling of cryptocurrency-fiat pairs. Transaction times may also present a problem in the high frequency trading of cryptocurrencies, as current transaction times (even in the major cryptocurrency networks) may not be small enough to support a higher frequency strategy than that presented in this analysis – e.g. minute-by-minute trading.

In addition, we do not take into account transaction costs or fees involved in cryptocurrency trading. Similar to the buying and selling of traditional financial instruments, one will incur fees when buying and selling cryptocurrencies through dedicated exchanges. This means that when trading a cryptocurrency, a particular market or exchange price will not be the price at which the cryptocurrency will be traded at. It is likely that the true price that one can buy (sell) the currency at will be higher (lower) than the market price. The difficulty in incorporating such fees into a trading strategy is that the fees and costs vary depending on where the cryptocurrency is traded.

A general comparison between the returns from the active and passive trading strategies is shown in Fig. 8. Fig. 8(a) compares a passive portfolio using monthly varying weights versus fixed weights, and Fig. 8(b) compares all of the different active and passive

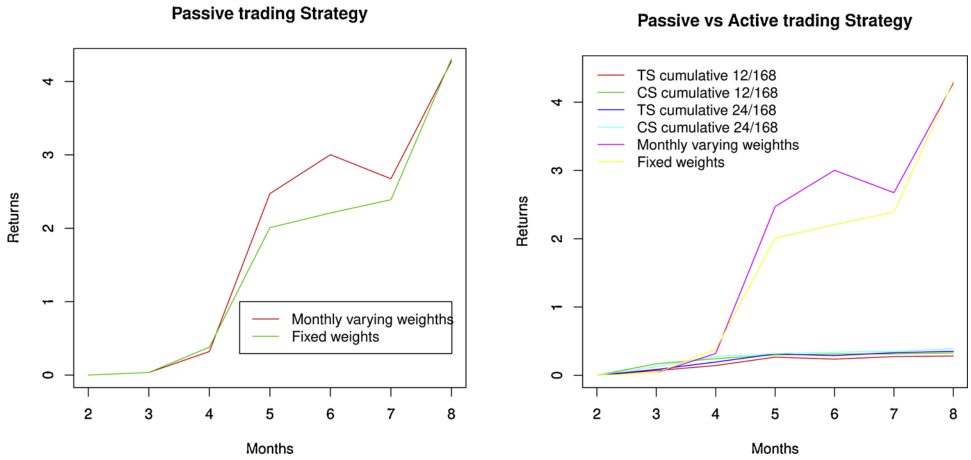

Fig. 8. (a) Comparison of the cumulative returns generated by a passive trading strategy using monthly varying weights (red) and fixed weights (green) (left); (b) comparison between the returns generated by different active and passive trading strategies (right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

strategies. The passive portfolio was implemented using the method as described at the end of Section 3, and it can be seen that the monthly varying weights outperforms the fixed weights method throughout the period studied. Furthermore, the returns for both methods are significant and increasing throughout the period, providing returns of over 300% towards the end of the period. Observing Fig. 8(b), it can be seen that the returns for both the passive and active strategies are relatively stable and similar for the first two months. However, after this period the passive strategies start to diverge from the active strategy and this difference becomes significant towards the end of our sample period. Overall, the general passive strategy outperforms all of the different active strategies studied in this paper over the whole period considered. This result could have been amplified by the fact that during this time, the whole cryptocurrency market was considered to have been in a bull market state with generally increasing prices.

4.1. Robustness check

As a first simple check for the robustness of our results from the trading strategies, we obtained another sample of an additional six months of the hourly prices of the top seven cryptocurrencies (ranked by market capitalisation) versus the US Dollar, spanning from August 2017 to February 2018 (which immediately follows the last observation in the original data analyzed). This period was chosen as it covered not only a 'boom' period (in the last few months of 2017) where the prices of all cryptocurrencies were generally increasing, but also a 'bust' period (at the end of 2017/start of 2018) where cryptocurrency prices peaked, and fell suddenly and rapidly. We are interested in whether the original results and methods still hold during this period when the cryptocurrency market experienced a significant change.

We performed the same analysis using the method described in Section 3 on the new sample of data and computed the corresponding plots for the daily and cumulative returns as in the original analysis, shown in Appendix Figs. 13–16. In general, the results agree with those in the original analysis where the two strategies appear to be able to generate positive cumulative returns, and here it is shown that this is true for other time periods. However, using this new sample period, we find that the trend of the cumulative returns differs slightly as there is more stability in the early time periods of the strategy, but the trend increases significantly as time passes.

By combining the plots of the cumulative returns of both strategies we obtain Fig. 9, for the four combinations of the short and long rolling standard deviations. Interestingly, we see that for this new sample period the cross sectional strategy outperforms the time series strategy in all four parameterisations, and even more significantly than in the original sample period. We also note that in the new sample period, the strategies are able to achieve returns approximately up to 0.6, which is higher than that in the original sample period. However, from Fig. 9 it appears that in this new sample period, holding and trading for longer is necessary in order to achieve significant returns.

Furthermore, combining the plots of the cumulative returns of the two strategies from both sample periods, in Fig. 10, we find more interesting results. In general, on the one hand, using a short rolling standard deviation of 12 h appears to generate slightly higher cumulative returns in the original sample period compared with the new sample period. On the other hand, using a short rolling standard deviation of 24 h appears to generate (significantly) higher cumulative returns in the new sample period compared with the original sample period, but only when using the cross sectional strategy over longer periods of time. Therefore, in the two sample periods we have two different strategies using slightly different parameterisations giving us the corresponding 'best' outcomes. This suggests that there may not be a 'one size fits all' strategy which could deliver the best trading performance over different time periods.

As with the analysis of the original sample period, we also provide a comparison, in Fig. 11, between the performance of the time series and cross sectional strategies, and the passive trading strategies described at the end of Section 3, over the new sample period.

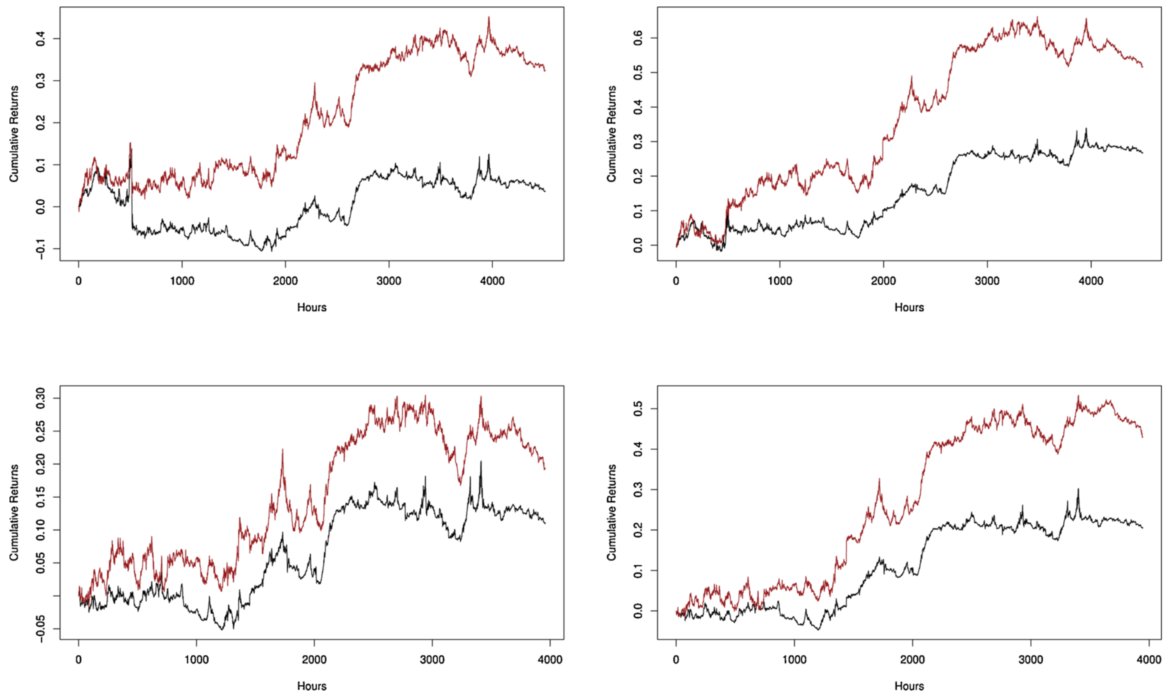

Fig. 9. Comparison of the cumulative returns (new sample period) from the time series portfolio method (black) and cross sectional portfolio method (red) using rolling standard deviations of: 12 and 168 h (top left); 24 and 168 h (top right); 12 and 720 (bottom left); 24 and 720 h (bottom right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

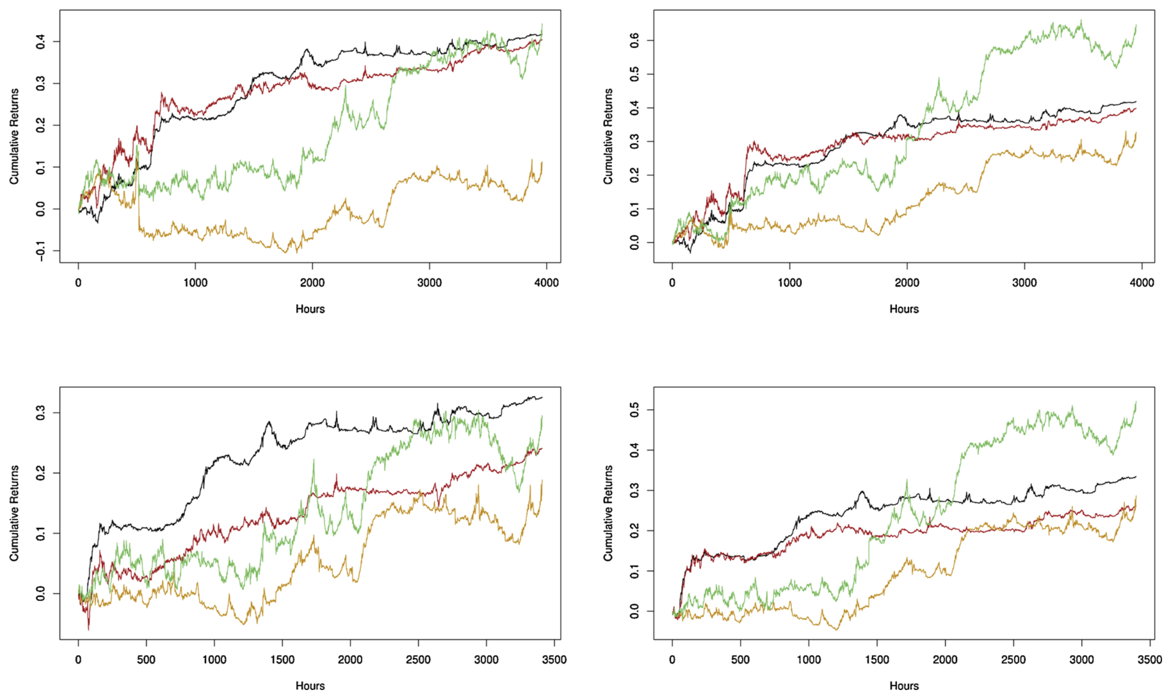

Fig. 10. Comparison of the cumulative returns (original sample period) from the time series portfolio method (black) and cross sectional portfolio method (red), and the cumulative returns (new sample period) from the time series portfolio method (yellow) and cross sectional portfolio method (green), using rolling standard deviations of: 12 and 168 h (top left); 24 and 168 h (top right); 12 and 720 (bottom left); 24 and 720 h (bottom right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

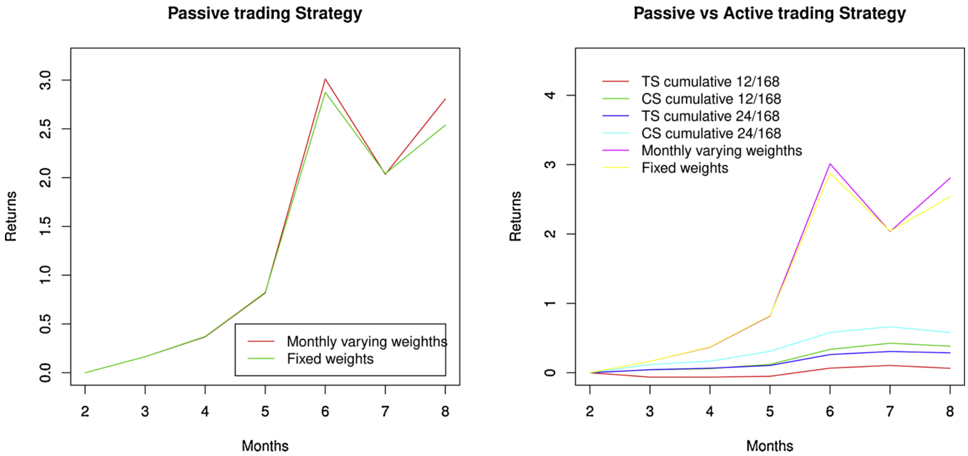

Fig. 11. (a) Comparison of the cumulative returns (new sample period) generated by a passive trading strategy using monthly varying weights (red) and fixed weights (green) (left); (b) comparison between the returns (new sample period) generated by different active and passive trading strategies (right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

We find that the comparison is very similar to that for the original sample period, where it is clear that the passive trading strategies clearly outperform the two momentum strategies regardless of the parameterisations of the strategies. In addition, from Figs. 9 and 11, we find that the state of the cryptocurrency markets is reflected in the trends of the cumulative returns. Towards the end of the new sample period (end of 2017 through to the beginning of 2018), the prices of cryptocurrencies saw huge increases but also saw significant crashes in the prices – which are indicated by the significant dips in the trends of the cumulative returns. Although all of the strategies appear to be influenced by this, the magnitude of the effect appears to be greater for the passive strategy, which is logical since the passive strategies are rebalanced monthly as opposed to the momentum strategies which are rebalanced hourly.

As a second simple check for the robustness of our original results, we computed the performance of the two strategies on our original sample, but rather than using the signal to determine the buying and selling of the cryptocurrencies, we base this decision on the returns of the cryptocurrencies. In both strategies, we still assume that the portfolios are rebalanced every hour. The modification for the time series strategy is as follows: after the portfolio is reset, an investment is made in each of the cryptocurrencies according to the sign of their corresponding returns in the previous period. If the previous return was positive then this indicates that a purchase of 1/7 units of US Dollars of the cryptocurrency should be made; if the previous return was negative then this indicates that a sale of 1/7 units of US Dollars of the cryptocurrency should be made; if the previous return was equal to zero then this indicates that no investment should be made. This theoretically generates a return $R_{\mathrm{TS}',t}$ in a time period t (when the portfolio is reset), from an investment at time $t-1$, for each cryptocurrency, of

$$R_{\mathrm{TS}',t} = \begin{cases} \frac{1}{7} \times \frac{1}{P_{t-1}} \times R_t & \text{if } R_{t-1} > 0 \\ -\frac{1}{7} \times \frac{1}{P_{t-1}} \times R_t & \text{if } R_{t-1} < 0\text{'} \\ 0 & \text{if } R_{t-1} = 0 \end{cases}$$

when $\frac{1}{P_{t-1}}$ denotes the indexed exchange rate of one US Dollar to the respective cryptocurrency at time $t-1$, R_t denotes the log one-period returns of the indexed exchange rate of the respective cryptocurrency at time t, and R_{t-1} denotes the log one-period returns of the indexed exchange rate of the respective cryptocurrency at time $t-1$ (the previous period return).

The modification of the cross sectional strategy is straightforward, as the method follows that as described in Section 3, with the only difference being how we rank the cryptocurrencies. When the returns of each cryptocurrency at some time $t-1$ are computed, the cryptocurrencies are instead ranked by their returns from largest to smallest. The investment in the cryptocurrencies is then identical to the original method, where for the top three cryptocurrencies a purchase of $\frac{1}{6}$ units of US Dollars of each cryptocurrency should be made; for the bottom three cryptocurrencies a sale of $\frac{1}{6}$ units of US Dollars of each cryptocurrency should be made. This theoretically generates a return $R_{\mathrm{CS}',t}$ in a time period t (when the portfolio is reset), from an investment at time $t-1$, of

$$R_{\mathrm{CS}'_{\mathrm{high}},t} = R_{\mathrm{CS}_{\mathrm{high}},t}, \tag{10}$$

for the three cryptocurrencies with the largest returns at $t-1$, and

$$R_{\mathrm{CS}'_{\mathrm{low}},t} = R_{\mathrm{CS}_{\mathrm{low}},t}, \tag{11}$$

for the three cryptocurrencies with the smallest returns at $t-1$.

As in Section 3, we are able to compute the total hourly returns (on all investments made at $t-1$) at each time period t, when using the two modified strategies, by simply summing the returns $R_{\mathrm{TS}',t}$ of each cryptocurrrency at time t (time series), or by summing

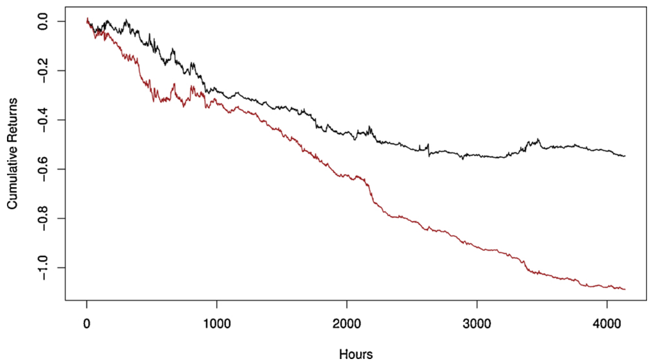

Fig. 12. Comparison of the cumulative returns (original sample period) from the returns-based time series portfolio method (black) and returns-based cross sectional portfolio method (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the three high returns $R_{\mathrm{CS}'_{\mathrm{high}},t}$ and three low returns $R_{\mathrm{CS}'_{\mathrm{low}},t}$ (cross sectional). Fig. 12 plots the cumulative returns generated by the two returns-based momentum strategies over the original sample period. It is immediately clear that the two returns-based strategies perform poorly when compared to the strategies based on signals computed from moving averages, using any of the combinations of parameter values. Both of the returns-based strategies generate negative cumulative returns over the whole sample period, and the losses become greater the longer the strategy continues – with the cross sectional strategy performing significantly worse than the time series strategy.

Out of interest, we investigated further the returns-based time series strategy. We computed the cumulative returns (not shown) for the different cases of applying the strategy to only the top one, top two, top three, etc. cryptocurrencies after rebalancing every hour. For example, considering only the top n cryptocurrencies means that at each hour an investment according to the returns-based time series strategy is made in the n cryptocurrencies with the largest returns. Interestingly, we found that up to the case of considering the top five cryptocurrencies, the cumulative returns generated by the returns-based time series strategy over the original sample period were positive, and in some cases significantly greater than those generated by the original time series strategy based on the signal.

However, in the case where the top six (or all seven) cryptocurrencies are considered the cumulative returns were negative (and significant). This suggests that (in general) the signs of the returns of the two cryptocurrencies with the lowest returns at some time $t-1$ become reversed at time t – e.g. $R_{t-1} > 0$ at $t-1$ and $R_{t-1} < 0$ at t, and vice versa. It would appear that this is happening frequently enough that according to the strategy, the investments made in these cryptocurrencies will be incorrect, and the losses (negative returns) are significant enough to cancel out (and exceed) any positive returns generated by investments in the other cryptocurrencies.

Our simple robustness checks appear to: (i) support the idea that the time series and cross sectional momentum trading strategies could theoretically be used to generate positive returns; (ii) suggest that the signal-based momentum strategies outperform the equivalent returns-based momentum strategies. However, these results and those in the main analysis have been obtained ex-post (after we have observed the data). We note that it may be difficult for one to determine the best strategy prior to a period of investment. For example, Fig. 11 showed that over two different time periods the largest cumulative returns (in each period) were generated by slightly different parameters in the strategies. Indeed, we are able to see this result now that we have access to the historical data, however, it is unlikely that one would be able to determine this before trading.

5. Conclusion

We have analyzed the momentum trading strategy, one of the oldest and simplest financial trading strategies, and its applicability to cryptocurrency trading. In particular, we have looked at adapting the simple technique to high frequency cryptocurrency trading. Our analysis used the hourly prices of the top seven cryptocurrencies (by market capitalisation) versus the US Dollar over approximately six months, from February 2017 to August 2017, and looked at two variations of the momentum method. The results obtained indicate that, in theory, it is possible to adapt this simple strategy to higher frequency financial data and still achieve positive results.

The best result that we were able to achieve was a cumulative return of approximately 0.4 (in terms of indexed prices) when using the time series strategy, over a test period of just under six months. This is in comparison to a cumulative return of around 0.9 in Rohrbach et al. (2017) using the time series strategy on daily cryptocurrency prices, over an approximate one and a half year period. We believe that this shows the potential for the momentum strategy to be used in cryptocurrency trading in a high frequency setting. A passive strategy portfolio computed using two different methods was seen to generate abnormal returns of over 300% towards the end of the sample period. In a comparison between the passive and active portfolios, the returns from the passive portfolio diverge from the active portfolio and this becomes increasingly more significant towards the end of our sample period. We believe that this may be due to the bull market run in the cryptocurrency market during that time.

To check the robustness of our results, we applied the two variations of the momentum strategies to another sample period, covering approximately the six months immediately following the original sample. We found similar results where the two strategies were able to achieve positive returns, and in a particular case when using the cross sectional strategy these returns reached approximately 0.6. We also compared the two momentum strategies based on signals (derived from exponential moving averages) to the same strategies modified to be based on returns, and found that the strategies based on signals outperform the same strategies based on returns. However, as mentioned in our discussion in Section 4, there currently exist many factors which may restrict the proper implementation of the trading strategy presented. These include limited true short selling facilities, transaction costs, and confirmation times (not accounted for in our analysis). We note that transaction and trading costs should be considered in any further analysis to confirm whether the strategies could be truly profitable.

Nevertheless, direct extensions to the current work could include looking into exactly which currencies are omitted at each time period in the cross sectional strategy. Since only the top three and bottom three cryptocurrencies, respectively, with the highest and lowest trend signals are utilized at each time period, it would be interesting to see whether there are any patterns which show that only some currencies are being omitted, or whether some are omitted more frequently than others. In addition, increasing the number of cryptocurrencies in the data set being tested may give us different results especially in the cross sectional strategy. Further comparisons between data of even higher frequency could be made, i.e. 30 min exchange rates or even minute by minute exchange rates; testing of more combinations of short and long rolling standard deviations could be used to investigate whether there exists an optimal strategy when using both the time series and cross sectional strategies.

Finally, another interesting factor would be to consider the time of entry into the market at which to start trading and also the length of the trading/holding period. The results from the analysis on the two sample periods suggest that using the same strategy may yield different levels of returns depending on the time at which one starts trading. In addition, the length of the trading period appears to influence the level of returns achievable. For example, when using the same strategy on two different sample periods, trading for a relatively short period of time generates levels of returns which are greater in the earlier period. However, if one keeps applying the strategy over a longer period of time, the levels of returns generated are greater in the later sample period.

Authors' contribution

Jeffrey Chu and Stephen Chan: conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, supervision, validation, writing – original draft, writing – review & editing.

Yuanyuan Zhang: conceptualization, data curation formal analysis, investigation, methodology, project administration, resources, software, validation, writing – original draft, writing – review & editing.

Appendix A

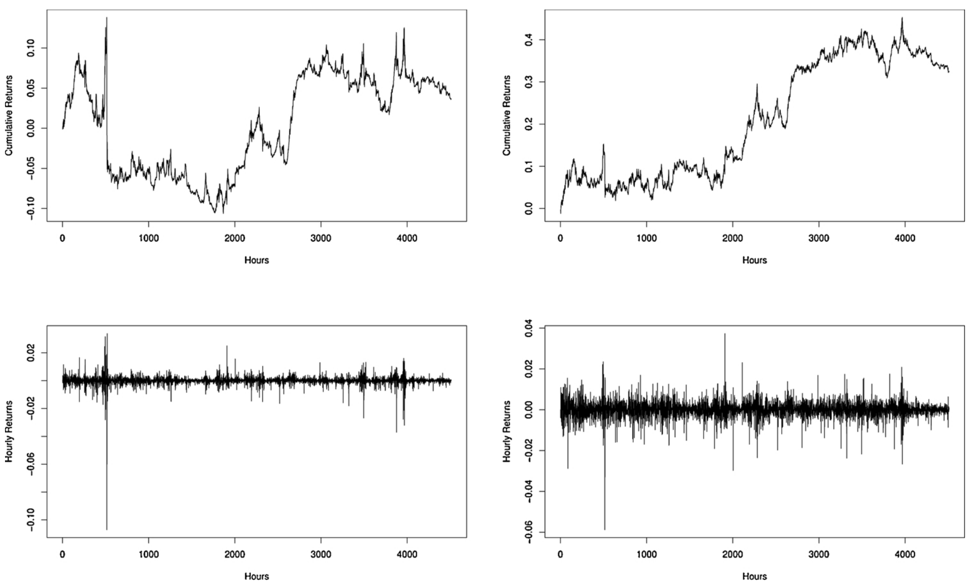

Fig. 13. Cumulative (top) and daily (bottom) returns, using rolling standard deviations of 12 and 168 h, using the time series portfolio method (left) and cross sectional portfolio method (right).

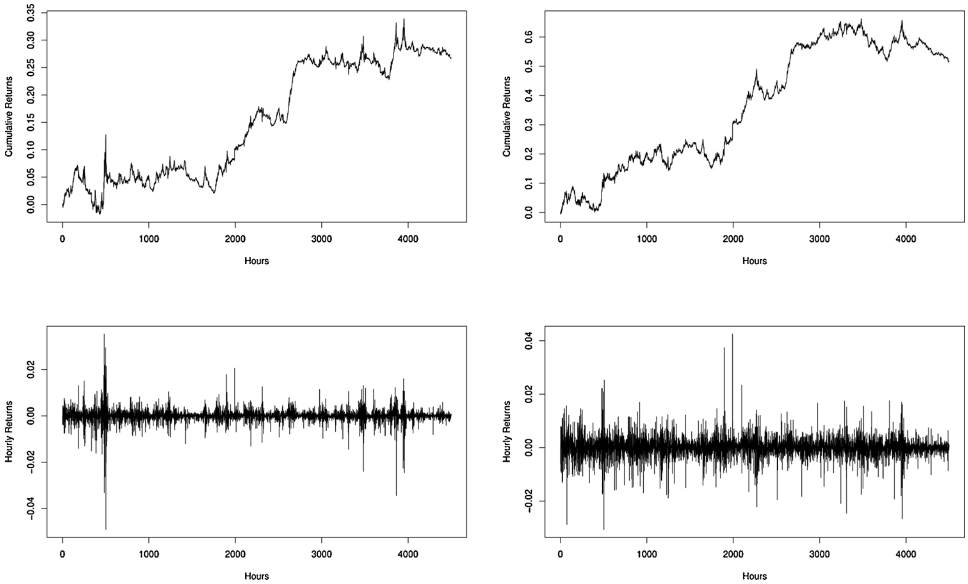

Fig. 14. Cumulative (top) and daily (bottom) returns, using rolling standard deviations of 24 and 168 h, using the time series portfolio method (left) and cross sectional portfolio method (right).

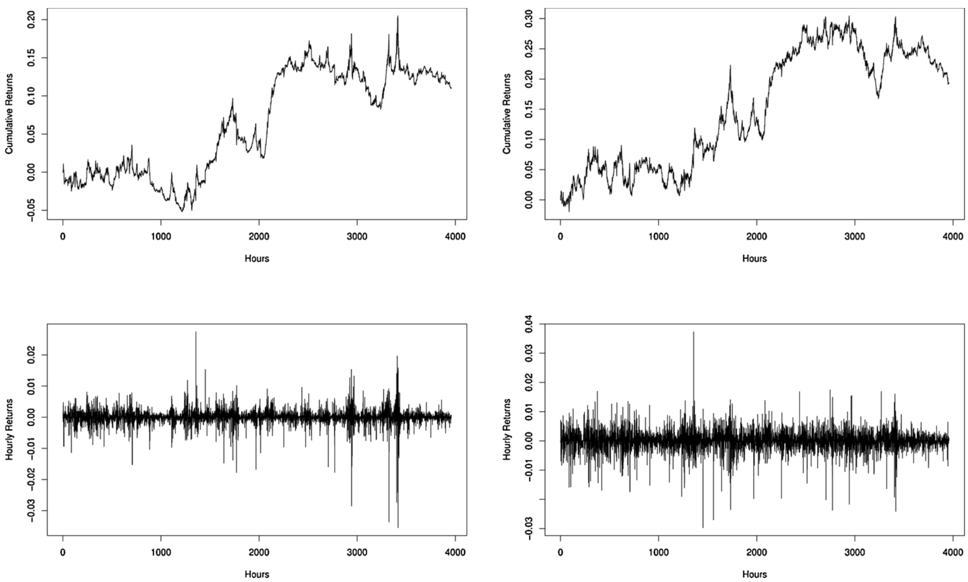

Fig. 15. Cumulative (top) and daily (bottom) returns, using rolling standard deviations of 12 and 720 h, using the time series portfolio method (left) and cross sectional portfolio method (right).

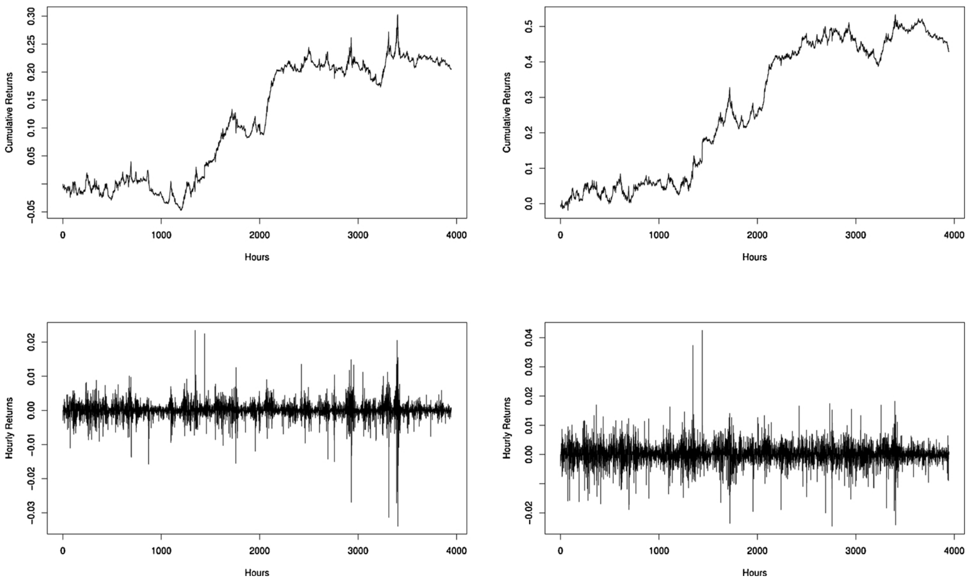

Fig. 16. Cumulative (top) and daily (bottom) returns, using rolling standard deviations of 24 and 720 h, using the time series portfolio method (left) and cross sectional portfolio method (right).

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