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On the Market Efficiency and Liquidity of High-Frequency Cryptocurrencies in a Bull and Bear Market

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Abstract: The market for cryptocurrencies has experienced extremely turbulent conditions in recent times, and we can clearly identify strong bull and bear market phenomena over the past year. In this paper, we utilise algorithms for detecting turnings points to identify both bull and bear phases in high-frequency markets for the three largest cryptocurrencies of Bitcoin, Ethereum, and Litecoin. We also examine the market efficiency and liquidity of the selected cryptocurrencies during these periods using high-frequency data. Our findings show that the hourly returns of the three cryptocurrencies during a bull market indicate market efficiency when using the detrended-fluctuation-analysis (DFA) method to analyse the Hurst exponent with a rolling window. However, when conditions turn and there is a bear-market period, we see signs of a more inefficient market. Furthermore, our results indicated differences between the cryptocurrencies in terms of their liquidity during the two market states. Moving from a bull to a bear market, Ethereum and Litecoin appear to become more illiquid, as opposed to Bitcoin, which appears to become more liquid. The motivation to study the high-frequency cryptocurrency market came from the increasing availability of higher-frequency cryptocurrency-pricing data. However, it also comes from a movement towards higher-frequency trading of cryptocurrency. In addition, the efficiency of cryptocurrency markets relates not only to whether prices are predictable and arbitrage opportunities exist, but, more widely, to topics such as testing the profitability of trading strategies and determining the maturity of cryptocurrency markets.

Keywords: Bitcoin; Ethereum; market liquidity; Hurst exponent; cryptocurrency; high frequency

1. Introduction

Recently, the market for cryptocurrencies has exhibited one of the most volatile periods in its history. While the total market capitalisation for cryptocurrencies reached a record high of over USD 800 billion in the last quarter of 2017, it was followed by a massive correction in the market leading to significantly reduced market capitalisation, which now stands at under USD 100 billion. This clearly suggests that the market has experienced a bull (cryptocurrency-price rising, precrisis) and bear (cryptocurrency-price falling, crisis) market throughout this period. Overspeculation, and interest from academics and those in the industry in this new financial technology are a few reasons behind this recent market phenomenon.

Over the past few years, the cryptocurrency literature has been rapidly expanding. The general literature on cryptocurrencies covers topics including (but not limited to) statistical analysis, modelling,

and predicting the Bitcoin/USD exchange rate, measuring the volatility of the Bitcoin exchange rate against different financial assets and commodities, stylised facts of cryptocurrencies, and the market efficiency of cryptocurrencies. [Chu et al. \(2015\)](#) provided the first statistical and risk modelling analysis on Bitcoin returns. The generalized hyperbolic distribution provided the best fit; [Glaser et al. \(2014\)](#) investigated whether Bitcoin users see it as a currency or asset, and found that most uninformed users were not interested in Bitcoin as a transaction system but instead saw it as an alternative investment method. [Kristoufek \(2013\)](#) investigated the relationship between Bitcoin prices and search queries from Google and Wikipedia. They found that there was a significant positive correlation between prices and search queries, and that search queries had asymmetric effects on Bitcoin prices depending on whether prices were above or below the short-term trend. The significant volatility in Bitcoin prices and returns cannot simply be explained by economic or financial theory. [Sapuric and Kokkinaki \(2014\)](#) analysed the volatility of the exchange rate of Bitcoin during its early years and found that it was significantly greater than that of major exchange rates. However, when they accounted for transaction volume, volatility appeared to be more stable. [Baur et al. \(2018\)](#) analysed the statistical properties of Bitcoin and found that they were “uncorrelated with traditional asset classes such as stocks, bonds, and commodities, both in normal times and in periods of financial turmoil”. In addition, the authors found that Bitcoin is primarily used as an investment asset and not as a currency. [Briere et al. \(2015\)](#) investigated Bitcoin from an investment perspective and found that it had significantly high average return and volatility, and little correlation with traditional financial assets. Results showed that, by including Bitcoin in well-diversified portfolios, the risk-return trade-off could be significantly improved.

The efficient market hypothesis (EMH) is a core and fundamental concept used in finance that was introduced by [Malkiel and Fama \(1970\)](#) through modelling financial data. There are three main forms of efficiency, with the most common being the weak form. The weak form states that investors cannot use historical-price information to make future-price predictions. The importance of understanding market efficiency can be beneficial to investors, academics, and financial practitioners, as historical-price pattern information can assist in the greater understanding or discovery of arbitrage returns. On the other hand, liquidity is a concept of how easily capital and assets can be traded without causing a dramatic change in an asset's price. In general, an illiquid asset would procure a higher bid ask spread and transaction cost, increasing the cost for speculators and investors to trade. Hence, if cryptocurrency markets are very illiquid, this results in market inefficiency, as the lack of market makers and traders causes a delay in market participants acting on new information.

Many attempts were made so far to study the market efficiency of various cryptocurrency markets, but the vast majority of the known work has been exclusively directed towards the Bitcoin market. For example, [Bariviera \(2017\)](#) studied the long-range memory of the Bitcoin market by analysing the Hurst exponent via the R/S and detrended-fluctuation-analysis (DFA) methods, and confirmed that daily volatility exhibits long-range memory; [Alvarez-Ramirez et al. \(2018\)](#) implemented the DFA method to estimate the long-range dependence of Bitcoin and found that the Bitcoin market exhibited periods of efficiency, alternating in different periods; [Tiwari et al. \(2018\)](#) reported that the Bitcoin market is informationally efficient, by using a battery of robust long-range dependence estimators; [Khuntia and Pattanayak \(2018\)](#) examined the efficiency of the Bitcoin market by using the Dominguez–Lobato consistent test and generalized spectral test, and concluded that dynamic efficiency in the Bitcoin market actually follows the proposition of adaptive market hypothesis (AMH); [Jiang et al. \(2018\)](#) employed the generalised Hurst exponent to investigate long-term memory in the Bitcoin market, and results suggested that the Bitcoin market was inefficient over the whole sample period; [Zhang et al. \(2018a\)](#) illustrated that the nine most popular cryptocurrency markets were inefficient by employing a battery of efficiency tests, and the MF-DFA and MF-DCCA approaches; [Zhang et al. \(2018b\)](#) analysed the stylised facts of cryptocurrencies in terms of long-range dependence by using the Hurst exponent with both the R/S and DFA methods for high-frequency-return data of the four most popular cryptocurrencies, while features of dependence between the different cryptocurrencies were also provided; [Chu et al. \(2019\)](#) analysed the efficiency of the high-frequency

markets of the two largest cryptocurrencies, Bitcoin and Ethereum, versus the euro and US dollar, by investigating the existence of the AMH.

Our main motivation was to analyse and understand market-efficiency patterns and liquidity behaviour during a bull (precrisis) and bear (crisis) market for cryptocurrencies. These periods are very intriguing as they represent different market conditions. The main contributions of this paper are: (i) utilising algorithms for detecting turning points to identify bull and bear phases for the three largest cryptocurrencies of Bitcoin, Ethereum and Litecoin in high-frequency (hourly) markets; and (ii) analysing and understanding the characteristics of market efficiency and liquidity in high-frequency cryptocurrency returns during a bull or bear market. This is the first study of detecting bull and bear periods in high-frequency cryptocurrency markets, and analysing their market efficiency and liquidity during such periods.

For each cryptocurrency, we analysed data from 1 July 2017 to 19 September 2018. This time period was divided into two subperiods, corresponding to a bull market (precrisis period) from 1 July 2017 to 16 January 2018 (4789 observations), and a bear market (crisis period) from 17 January 2018 to 19 September 2018 (5888 observations). Sections 2 and 3 provide a detailed justification of how the bull and bear markets were identified.

For each cryptocurrency, we performed analysis by using two different methods. The first was to apply the DFA method to compute the Hurst exponent over a rolling window during a bull and bear market to analyse the behaviour of the high-frequency (hourly) returns of Ethereum, Bitcoin and Litecoin. The DFA method is most commonly implemented by using a rolling-window approach for analysing the Hurst exponent in financial time series (see, for example, [Matos et al. 2008](#), [Grech and Mazur 2004](#), and [Carbone et al. 2004](#)). The second was to use a series of tests, presented in Section 2, which examined the efficient market hypothesis within fixed periods (bull and bear markets). A rolling-window approach splits a dataset into subsamples of a specific size rather than analysing the whole data sample in one process. The initial subsample is analysed before the next most recent data are added to the subsample, and the earliest data in the subsample are removed. This process is then repeated until the subsample reaches the most recent data in the whole sample. A conventional fixed-period method analyses the whole data sample in one go.

The contents of the paper are organised as follows. The algorithms used in detecting bull and bear markets in cryptocurrencies and the methods used to measure the long-range memory, liquidity, and market efficiency of cryptocurrencies in a bull and bear market are discussed in Section 2. The three cryptocurrency datasets and their summary statistics are described in Section 3. Data analysis using a range of different methods, including analysis of the Hurst exponent, is presented in Section 4. Finally, conclusions are drawn in Section 5.

2. Method

2.1. Detecting Bull and Bear Markets

In the finance literature, there is no generally accepted formal definition of a bull or bear market. Therefore, in this paper, the considered time period was split into bull and bear phases in the cryptocurrency markets on the basis of two well-known algorithms: the algorithm of [Lunde and Timmermann \(2004\)](#) (filtering method) and the algorithm of [Bry and Boschan \(1971\)](#) (dating method). Both of these methods were designed to capture financial and business cycles. Here, we give a brief explanation of these two methods.

The [Lunde and Timmermann \(2004\)](#) algorithm is based on imposing a minimum on the price change since the last peak or trough. Let λ_1 be a scalar defining the threshold for a transition from a bear to bull market, and λ_2 be a threshold for a transition from a bull to bear market. Suppose X_t denotes the hourly price of a cryptocurrency at time t , and a trough in X has been detected at time

$t_0 \leq t$. A bull phase begins in the algorithm at time $t_0 + 1$. The algorithm first detects the maximum value in X at time $[t_0, t]$:

$$X_{t_0,t}^{\max} = \max \{X_{t_0}, X_{t_0+1}, \dots, X_t\}.$$

Then, the relative change in X is computed as

$$\delta_t = \frac{X_{t_0,t}^{\max} - X_t}{X_{t_0,t}^{\max}}.$$

If $\delta_t > \lambda_2$, this point is denoted as a new peak (maximum) occurring at t_{peak} in interval $[t_0, t]$. Then, $[t_0 + 1, t_{peak}]$ is labelled as a bull state period. By contrast, a Bear state period begins from $t_{peak} + 1$ and if a peak has been identified in X at time $t_0 \leq t$, then the algorithm finds the minimum value of X on the time interval $[t_0, t]$,

$$X_{t_0,t}^{\min} = \min \{X_{t_0}, X_{t_0+1}, \dots, X_t\}$$

and then the relative change in X is computed as

$$\delta_t = \frac{X_{t_0,t}^{\min} - X_t}{X_{t_0,t}^{\min}}.$$

If $\delta_t > \lambda_1$, this point is denoted as a new trough (minimum) occurring at t_{trough} in the interval $[t_0, t]$. Then, $[t_0 + 1, t_{trough}]$ is labelled as a bear period. A bull period begins from $t_{trough} + 1$. For more details on this method, see [Lunde and Timmermann \(2004\)](#).

The main objective of the [Bry and Boschan \(1971\)](#) algorithm is to detect turning points in a financial cycle. This method consists of two main steps: identifying the initial turning points in X , followed by guided censoring operations. First, one identifies a window of length τ_{window} months on either side of the date and defines a peak (trough) in X as a point higher (lower) than other points within the window. Next, censoring requires eliminating peaks and troughs in the first and last τ_{censor} months; eliminating phases that last less than τ_{phase} months; and eliminating cycles that last less than τ_{cycles} months. We repeated the procedure of the censoring operation many times, until the sequence of turning points satisfied all constraints. For more details on this method, see [Bry and Boschan \(1971\)](#).

A major drawback of the [Bry and Boschan \(1971\)](#) method is that it is mostly applied to monthly frequency data, and it is very sensitive to data frequency. On the other hand, one can just edit the parameters to account for the data frequency. Compared with the [Bry and Boschan \(1971\)](#) method, the [Lunde and Timmermann \(2004\)](#) method is not that sensitive when applied to either daily or hourly frequency data because parameters in the algorithm are computed as two relative changes in the cryptocurrency prices in the algorithm. Implementation of the two algorithms to our selected data is described in Section 3.

One may question if the use of these methods is adequate for analysing cryptocurrency markets or whether it can only be applied to traditional business cycles. To answer this question, it is best not to look specifically at the duration of business cycles and say whether cryptocurrency cycles are similar or not, but rather to look back at the algorithm itself (see Section 3). The algorithm determines bull and bear markets in any financial markets through the setting of a threshold relating to a level of price change that, if exceeded, represents a change in the market state. Hence, these methods are robust to application in any financial market, as discussed by [Bry and Boschan \(1971\)](#) and [Lunde and Timmermann \(2004\)](#).

2.2. Detrended Fluctuation Analysis (DFA) Method

We tested for long-range memory in the bull and bear markets of Ethereum, Bitcoin, and Litecoin by computing the Hurst exponent via the DFA method. The DFA method examines dependence in these markets, and was an indicator of random and nonrandom behaviour in our time series. Other methods for detecting long-range memory include R/S analysis, which is one of the most popular extended methods that can be used to estimate long-term memory in time-series data; however, it is not that stable. For instance, when a process under investigation has short memory, the R/S statistic may wrongly indicate the presence of long-term memory. The DFA method has been shown to be more suitable in dealing with nonstationary time-series data. In addition, as highlighted by [Grau-Carles \(2000\)](#), the DFA method avoids the spurious detection of long-range dependence. Hence, this is the main reason why chose to use the method. The computation of the Hurst exponent was conducted using the R statistical software package ([R Development Core Team 2019](#)). We followed the method presented in Section 2.1 of [Zhang et al. \(2018b\)](#), to compute Hurst exponent values, using the default parameters given in the procedure, and a rolling window of 720 (approximately one month) lagged data points. Further details on these methods applied to cryptocurrency data can be found in [Zhang et al. \(2018b\)](#).

The values that the Hurst exponent (α) could take range from 0 to 1. A value of $\alpha = 0.5$ indicates that the time series follows a random walk and does not exhibit a long memory. However, if $\alpha \neq 0.5$, this indicates that the considered time series exhibits evidence of long-term correlations. If $0.5 < \alpha < 1$, the series indicates trend-reinforcing behaviour; if $0 < \alpha < 0.5$, the series exhibits antipersistence behaviour. The stochastic behaviour of the Hurst exponent computed using the DFA method for hourly returns of Ethereum, Bitcoin, and Litecoin in bull and bear markets is illustrated in Section 4.

2.3. Efficiency Market Hypothesis Tests

Other methods used to test the efficiency market hypothesis include the Ljung–Box test ([Ljung and Box 1978](#)) that examines the null hypothesis of no autocorrelation; and the Wald–Wolfowitz Runs Test ([Wald and Wolfowitz 1940](#)) and the Bartels Rank Test ([Bartels, 1982](#)), both testing the null hypothesis of independence of the returns; the Wild Bootstrapping of Automatic Variance Ratio Test ([Kim 2009](#)) and the Spectral shape tests ([Durlauf 1991](#)), testing the null hypothesis that returns follow a random walk; and the Automatic Portmanteau Test ([Escanciano and Lobato 2009](#)), testing a null hypothesis of serial correlation.

2.4. Illiquidity Measure

The Amihud illiquidity (ILLIQ) ratio ([Amihud 2002](#)) is a common measure used to calculate the degree of stock liquidity. Here, we applied this measure to compute and compare the liquidity of cryptocurrencies during bull and bear markets. We could also interpret this ratio as a measure of price impact because it represents an hourly price response associated with one dollar of trading volume. This illiquidity measure was chosen for its simplicity and robustness as it requires only high-frequency trade data. More importantly, other liquidity measures require microstructure data on cryptocurrencies, and these data are not freely available, as the market is still in its infancy. The Amihud illiquidity ratio is defined as

$$ILLIQ_{iT} = 1/D_{iT} \sum_{t=1}^{D_{iT}} \frac{|R_{it}|}{VOLD_{it}}, \quad (1)$$

where D_{iT} denotes the number of traded hours in cryptocurrency i in year T , R_{it} is the hourly return on cryptocurrency i in hour t in USD, and $VOLD_{it}$ is the hourly volume in dollars (price at time $t \times$ volume at time t) on cryptocurrency i in hour t .

3. Data

In this paper, the datasets that we used consisted of historical high-frequency (hourly) prices of cryptocurrencies versus the US Dollar (USD) from 11:00 on 11 July 2017 to 00:00 on 19 September 2018 inclusive. The data were obtained from [CryptoCompare \(2018\)](#), and our analysis was limited to data that were available for download at the time. We chose cryptocurrencies for our analysis on the basis of the most popular cryptocurrencies traded on the GDAX exchange during that time, namely, Bitcoin, Ethereum, and Litecoin. These three cryptocurrencies accounted for around 80% of total market capitalisation for cryptocurrencies during that period, and we could therefore assume that the used datasets provide an adequate representation of the market. [Chan et al. \(2017\)](#) provides more details on the individual cryptocurrencies.

Before analysis, our preliminary approach in determining the bull and bear run period was to first identify the highest point (peak) in the dataset, which occurred on 16 January 2018. We then classified all data points prior to the peak (from 1 July 2017 to 16 January 2018) as being part of a general bull run in the market, and all points after the peak (17 January 2018 to 19 September 2018) as part of a general bear market run. However, to theoretically justify our selected periods, we implemented the [Bry and Boschan \(1971\)](#) and [Lunde and Timmermann \(2004\)](#) algorithms using the parameter values mentioned in Section 2 for detecting bull and bear periods.

There are numerous software packages that could be implemented to detect bull and bear markets in financial data, and in this analysis we use the R statistical software package (2019). To implement the ‘dating’ and ‘filtering’ algorithm methods introduced by [Bry and Boschan \(1971\)](#), and [Lunde and Timmermann \(2004\)](#), respectively, in R, we used R package `bbdetection`. The parameter values for the two methods were set using the two commands `setpar_dating_alg` and `setpar_filtering_alg`, respectively. For the dating algorithm, we selected parameter values of

$$\tau_{window} = 168, \tau_{censor} = 24, \tau_{phase} = 12, \tau_{cycle} = 12, \theta = 20.$$

For the filtering algorithm, we selected parameters of

$$\lambda_1 = 20, \lambda_2 = 20$$

Our reasoning for the values of λ_1 , λ_2 , and θ was to have a consistent threshold relating to price changes in both methods to detect peaks and troughs to determine the start and end of bull- and bear-market states. In the dating algorithm, τ_{window} was selected so that, at each time point, only turning points in the one week before and after were considered. The remainder of the parameter values were chosen to remove bull- and bear-market states that were only short-lived and insignificant.

Figure 1 plots the results of these algorithms in detecting bull and bear periods in cryptocurrency data. The shaded-white (grey) areas identify periods of a bull (bear) market run in the cryptocurrency data. The top-left (-right) diagram in Figure 1 shows the result through implementing the dating (filtering) algorithm, respectively, for Ethereum. The majority of the area before the peak for both approaches has a greater proportion of shaded-white areas than grey, which indicates that, in general, the market was a bull market. In contrast, the period after the peak sees a greater proportion of shaded-grey areas, which suggests that the market was more of a bear market in that period. Similar results were also seen for Bitcoin and Litecoin using the dating and filtering algorithms. Hence, the results used in this analysis support our preliminary results. This provides us with a reasonable case for selecting our chosen time periods for the bull and bear periods in our main analysis.

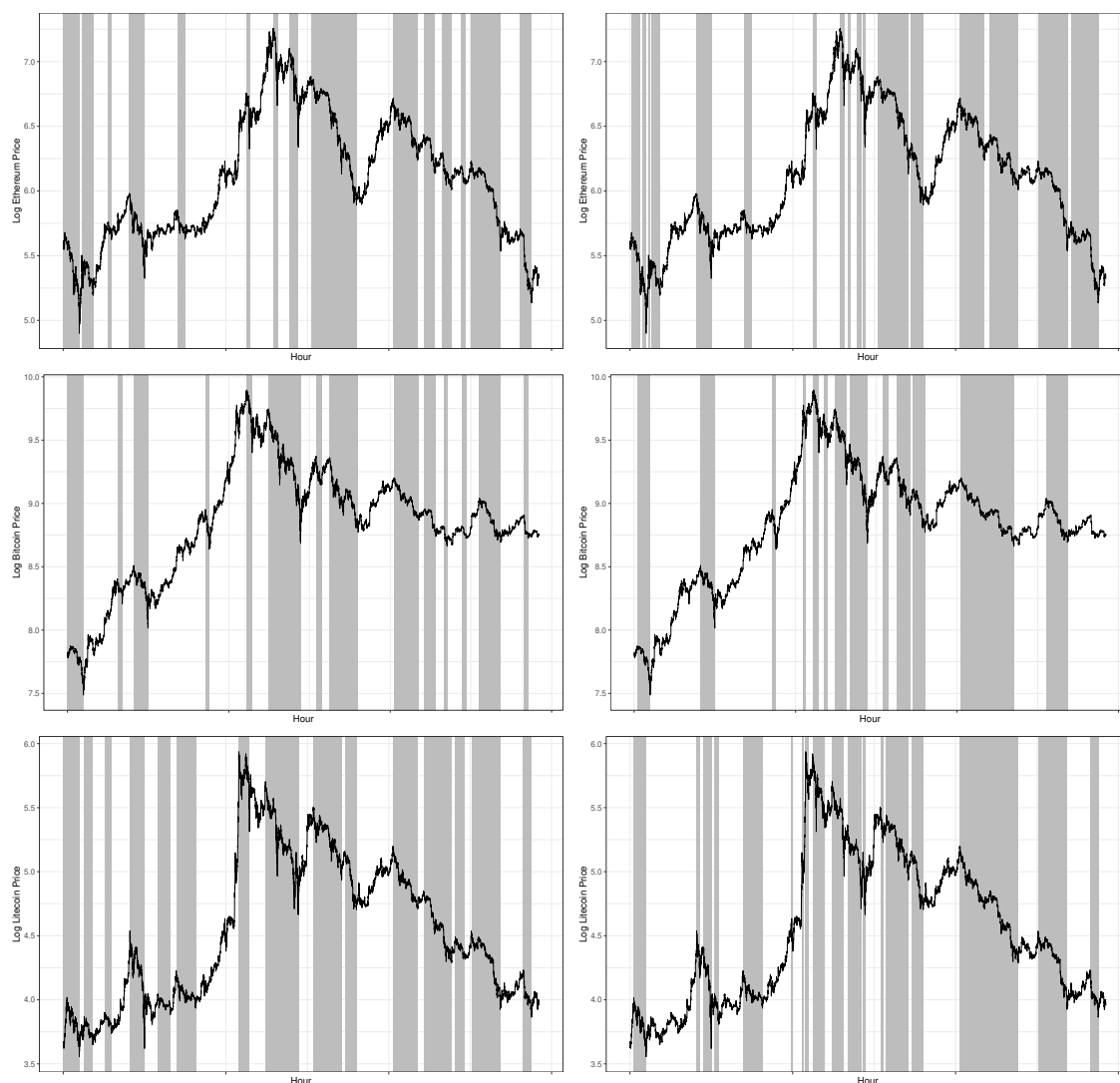


Figure 1. Plots indicating bull–bear periods using Ethereum (**top left**) dating and (**top right**) filtering algorithm, Bitcoin (**middle left**) dating and (**middle right**) filtering algorithm, and Litecoin (**bottom left**) dating and (**bottom right**) filtering algorithm. Bull and bear periods indicated by white and grey shaded areas, respectively.

Tables 1 and 2 provide summary statistics of log returns of high-frequency (hourly) market prices during a bull and bear market. In Table 1, the summary statistics of the log returns of the market-price index for Ethereum, Bitcoin, and Litecoin versus USD in a bull market are given. The BTC/USD index had the highest minimum, first quartile, median, and mean, while it had the lowest third quartile, maximum, and range. In contrast, the LTC/USD index had the lowest minimum, first quartile, and median, while it had the highest mean, third quartile, maximum, and range. Bitcoin was the only negatively skewed cryptocurrency. All cryptocurrencies showed significantly greater peakedness than normal distribution, and the LTC/USD index gave the highest kurtosis value. In terms of index spread, the values of standard deviation and variance for all cryptocurrencies were fairly similar (almost 0).

Table 1. Summary statistics of log returns of hourly market price index during a bull market in ETH/USD, BTC/USD and LTC/USD.

Statistics	ETH/USD	BTC/USD	LIT/USD
Observation size	4789	4789	4789
Minimum	−0.1596	−0.1316	−0.1951
Q1	−0.0053	−0.0048	−0.0063
Median	0.0002	0.0005	0.0000
Mean	0.0002	0.0003	0.0003
Q3	0.0058	0.0058	0.0060
Maximum	0.1398	0.1088	0.1825
Skewness	0.0628	−0.0964	0.8616
Kurtosis	12.1973	9.8589	18.7298
SD	0.0148	0.0126	0.0173
Variance	0.0002	0.0002	0.0003
CV	51.7825	39.4293	52.3381
Range	0.2994	0.2405	0.3776
IQR	0.0111	0.0105	0.0123

Table 2. Summary statistics of log returns of hourly market price index during bear market in ETH/USD, BTC/USD and LTC/USD.

Statistics	ETH/USD	BTC/USD	LIT/USD
Observation size	5888	5888	5888
Minimum	−0.0900	−0.0730	−0.1037
Q1	−0.0051	−0.0032	−0.0053
Median	0.0000	0.0000	−0.0003
Mean	−0.0003	−0.0001	−0.0002
Q3	0.0050	0.0031	0.0047
Maximum	0.1593	0.1086	0.1874
Skewness	0.6534	0.6156	1.0088
Kurtosis	15.1537	13.6283	16.4544
SD	0.0125	0.0100	0.0131
Variance	0.0002	0.0001	0.0002
CV	−46.3241	−101.9201	−60.7999
Range	0.2493	0.1816	0.2911
IQR	0.0101	0.0064	0.0100

Table 2 presents summary statistics of log returns of market price index for Ethereum, Bitcoin, and Litecoin versus USD during a bear market. Similar to Table 1, the BTC/USD index had the highest minimum, first quartile, median, and mean, while it had the lowest third quartile, maximum, and range. Litecoin had the lowest minimum, first quartile, and median, and the highest maximum and range. Once again, all cryptocurrencies showed significantly greater peakedness than normal distribution, and the LTC/USD index gave the highest kurtosis value. Compared with bull-market summary statistics, all cryptocurrencies were positively skewed, and Litecoin had the largest skewness value. With regard to variation, ETH/USD gave the greatest standard deviation and variance. Standard deviation and variance values of log returns for all cryptocurrencies were very small and close to 0.

By comparing Tables 1 and 2, there was significant difference in some statistical properties between bull and bear markets. Compared with the bull market, the values of the minimum, skewness, and kurtosis for all cryptocurrencies increased during the bear market. However, the coefficient of variation for all cryptocurrencies significantly decreased, changing from positive to negative values. The interquartile range (IQR) for all cryptocurrencies also decreased in the bear market, implying that the middle 50% of data during the bear market were less spread out.

4. Results and Discussion

Tables 3–5 show the results of the various test for the efficient market hypothesis on Ethereum, Bitcoin, and Litecoin, respectively. These tests were conducted over two fixed subperiods, during the bull market and during the bear market. In each case, corresponding *p*-values are shown. For the bull-market period, the majority of the *p*-values (with the exception of the Runs test for Ethereum and the AVR test for Litecoin) for all cryptocurrencies rejected the null hypotheses of no autocorrelation, independence, and random walk. Similarly, during the bear-market period, the majority of the *p*-values (with the exception of the Ljung–Box test and AVR test for Ethereum) for all cryptocurrencies rejected the null hypotheses of no autocorrelation, independence, and random walk. Overall, these tests indicated that high-frequency (hourly) cryptocurrency returns exhibited behaviour consistent with an inefficient market during both a bull and bear market. When compared to other financial markets, similar results can be seen, for example, [Gil-Alana et al. \(2018\)](#) noted that the Baltic stock market rejected the theory of market efficiency during the bull and bear markets; [Jiang and Li \(2019\)](#) investigated market efficiency for the Chinese, Japanese, and U.S. stock markets, and found market inefficiency in both the bull- and bear-market states, which could be explained by behavioural finance theory.

Table 3. Market-efficiency test for hourly returns of Ethereum during bull and bear market.

Test	Ljung–Box Test	Runs Test	Bartels Test	AVR Tests	SST	SST
Ethereum (Bull)	0.00591	0.174	0.000615	0.022	4.47×10^{-5}	3.38×10^{-4}
Ethereum (Bear)	0.297	1.41×10^{-6}	9.27×10^{-6}	0.566	0.00167	0.00366

Table 4. Market-efficiency test for hourly returns of Bitcoin during bull and bear market.

Test	Ljung–Box Test	Runs Test	Bartels Test	AVR Tests	SST	SST
Bitcoin (Bull)	0.0003	3.26×10^{-6}	6.01×10^{-4}	0.018	1.04×10^{-5}	6.65×10^{-5}
Bitcoin (Bear)	0.04676	4.44×10^{-16}	2.60×10^{-14}	0.062	7.63×10^{-4}	0.00131

Table 5. Market-efficiency test for hourly returns of Litecoin during bull and bear market.

Test	Ljung–Box Test	Runs Test	Bartels Test	AVR Tests	SST	SST
Litecoin (Bull)	0.0777	0.0128	0.0188	0.7	7.16×10^{-4}	0.00194
Litecoin (Bear)	9.33×10^{-4}	2.37×10^{-10}	2.08×10^{-9}	0.02	6.02×10^{-6}	2.08×10^{-5}

The results of Amihud’s illiquidity ratio are shown in Table 6. Results were multiplied by 10^8 for a simpler comparison, and this did not lead to loss of information. When comparing the three cryptocurrencies on the basis of the Amihud ratio, Bitcoin had the smallest value, followed by Ethereum and Litecoin. This illustrates that Bitcoin is the most liquid cryptocurrency. This result is consistent with our expectations, as Bitcoin holds the largest share of the cryptocurrency-market capitalisation, making it the most actively traded cryptocurrency. Other factors that led to Bitcoin being the most actively traded cryptocurrency include numerous trading platforms requiring users to hold Bitcoin before being able to trade other cryptocurrencies; the launch of Bitcoin futures, which allowed speculators to long and short Bitcoin and increased Bitcoin volatility; and the majority of exchanges providing other products, such as the trading of cryptocurrency pairs (e.g., BTC/ETH, BTC/LTC, BTC/XRP), with the majority of pairs involving Bitcoin.

Table 6. Amihud illiquidity ratio on hourly returns for Ethereum, Bitcoin, and Litecoin during bull and bear market.

Test	Amihud
Ethereum (Bull)	0.415756
Ethereum (Bear)	0.438561
Bitcoin (Bull)	0.275500
Bitcoin (Bear)	0.162648
Litecoin (Bull)	0.943289
Litecoin (Bear)	0.949993

When comparing bull- and bear-market liquidity and volatility, there was a strong relationship between liquidity and volatility for Ethereum and Litecoin. For Ethereum and Litecoin, market volatility decreases during a bear market, and the market becomes less liquid. However, results were different for Bitcoin, as market volatility decreases during a bear market, and Bitcoin becomes more liquid than in the bull market. This phenomenon could be explained by investors becoming irrational and worrying about the whole cryptocurrency market collapsing, leading to a majority of investors cashing out their cryptocurrency holdings. Most trading exchanges only allow cashing out cryptocurrencies through Bitcoin; therefore, this also causes Bitcoin to be traded by more active traders, which makes the market more liquid.

The long-range memory for all three cryptocurrencies during a bull and bear market was computed using the DFA method. The difference between this and previous methods is that this technique uses a rolling-window approach, as discussed in Section 2. A dotted black line in each plot was included to enable easier comparison between plots. Figure 2, illustrates the fluctuating behaviour of the Hurst exponent for the hourly returns of Ethereum, Bitcoin, and Litecoin during the different market periods. Ethereum and Bitcoin Hurst exponent values follow a similar pattern during the bull and bear market. In contrast, Litecoin results look slightly different. Throughout the bull period, Ethereum and Bitcoin generated a Hurst exponent of around 0.5, with Ethereum being slightly higher than Bitcoin. However, at around 2700 lags (bull period), the value significantly drops to below 0.4 before correcting and fluctuating back to around 0.5. In general, a Hurst exponent close to 0.5 indicates that the series is more random and resembles a random walk. This suggests that hourly Ethereum and Bitcoin returns are relatively efficient during a bull market. During the bear market, Ethereum and Bitcoin exhibit an increasing trend in the Hurst exponent as lag times increase. This indicates that the returns of both cryptocurrencies experience long-term positive autocorrelation. For Litecoin, the pattern of the Hurst exponent during a bull market is very close to 0.5 for the first 3000 lags, which illustrates that returns follow a random walk. However, after 3000 lags, the Hurst exponent suddenly increases to a value over 0.6, suggesting persistent behaviour. During a bear market, Litecoin exhibits a similar pattern to Bitcoin and Ethereum, suggesting that the market experiences long-term positive autocorrelation. Overall, we can conclude that, during a bull market, cryptocurrencies exhibit random-walk behaviour. However, when a bear market occurs, returns start to show persistent positive autocorrelation behaviour (market inefficiency). These results are also in line with those of Wang and Yang (2010), who identified intraday market inefficiency in heating-oil and natural-gas energy future markets during bull-market states, but not during bear markets.

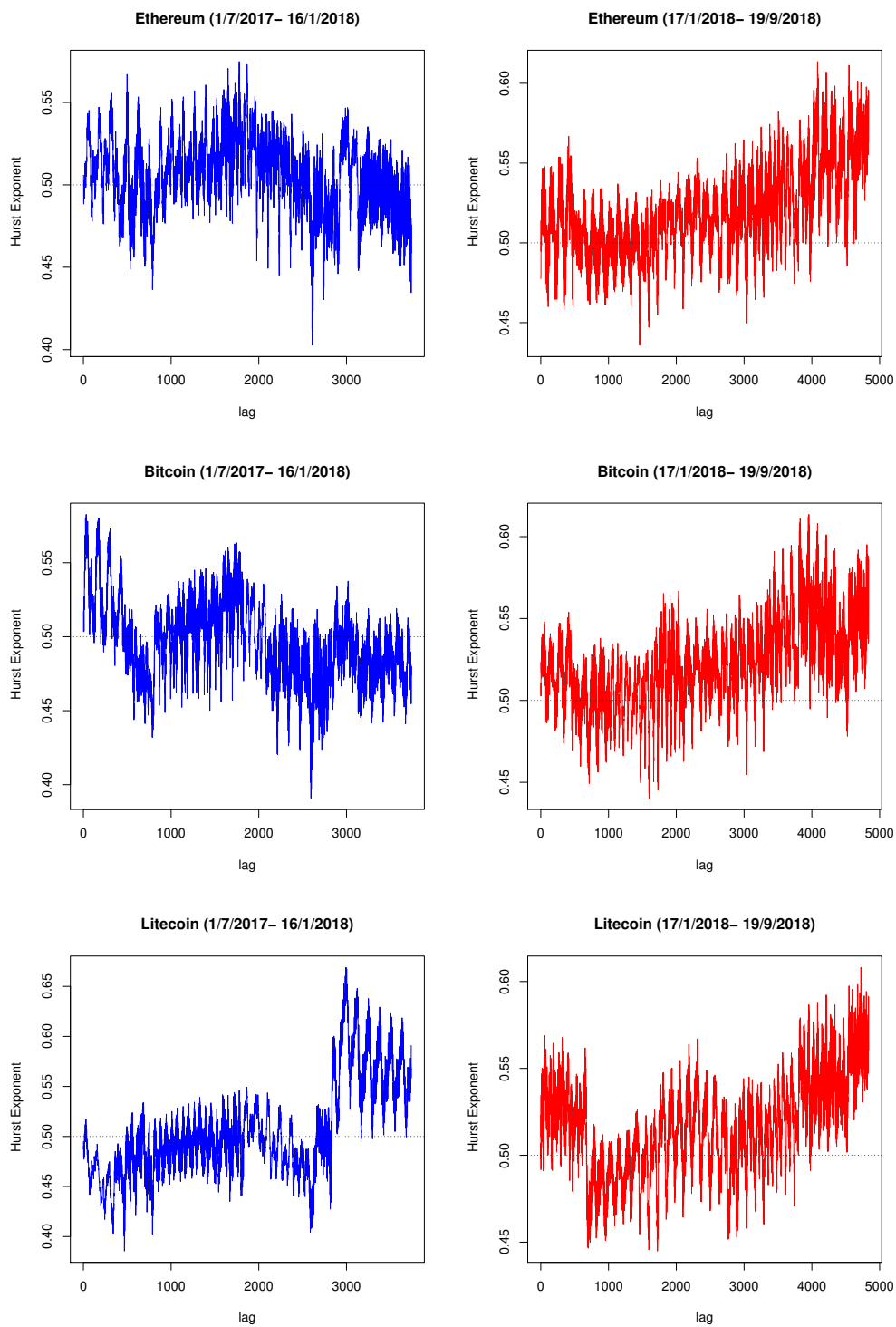


Figure 2. Plots of Hurst exponent of high-frequency 1 h log returns of (top left, top right) Ethereum, (middle left, middle right) Bitcoin, and (bottom left, bottom right) Litecoin using a sliding window of 720 lagged data points. Bull and bear markets indicated by blue and red lines, respectively.

A contrast in results from both methods during the bull-market phase could be interpreted in the following way. Analysis involving the Hurst exponent utilises a rolling-window approach; during these individual rolling windows (subsamples of a specific size) within the bull market, the cryptocurrency market had actually steadily grown with investors gradually entering the market, thus leading to an efficient-market phenomenon. However, if we look at the overall picture of the bull-market phase,

we see the market significantly rises; when considering the method that uses a fixed sample period, this appears to create an inefficient market. On the contrary, during the bear-market phase, the price consistently decreased throughout the whole period, which may have caused panic and irrational trading by investors, leading to a downward spiral in market prices, resulting in market inefficiency.

The actual methods and tests used here could also lead to result divergence due to the difference in tested samples in each case. For example, methods such as the Ljung–Box, Runs, and Bartels tests analyse all bull-/bear-market phase data as one, as opposed to the DFA method that analyses dynamic rolling data windows from the bull-/bear-market periods. In other words, the size of the samples analysed by the DFA method is smaller, but data points vary, while samples used in general tests are larger and data are fixed. Therefore, it is possible that the DFA method picks up variations within particular subsamples of return data (thus affecting results relating to market efficiency), which may be masked when considering bull-/bear-market samples as a whole. Furthermore, our results illustrate that, in a bear market, hourly Bitcoin returns become more liquid during this period of market inefficiency. In contrast, hourly Ethereum and Litecoin returns exhibit less liquidity in this period.

Here, we only tested the hypothesis of market efficiency through a range of different tests (including classical tests and the DFA method). We cannot claim that the DFA is better or more trustworthy, but results of DFA analysis suggest that the level of market efficiency is different in bull and bear markets. Although the Hurst exponent (as a proxy for market efficiency) shows general trends in bull and bear markets, there are shorter-term changes that are also captured, likely due to the rolling-window approach. One could run the classical tests over different sample periods, but a problem that remains is that classical tests only generate a p-value. This p-value only gives us an indication of whether we can reject or fail to reject the null hypothesis of tests for properties such as independence, autocorrelation, and random walk. This is in contrast to DFA analysis, which not only gives us a numerical value indicating deviations from market inefficiency, but could provide further information, such as trend-reinforcing or antipersistence behaviour.

5. Conclusions

We provided the first analysis for detecting bull and bear markets for the three largest cryptocurrencies of Bitcoin, Ethereum, and Litecoin in high-frequency (hourly) markets using algorithms on the basis of [Lunde and Timmermann \(2004\)](#) and [Bry and Boschan \(1971\)](#). Results from Section 4 showed that hourly returns of Ethereum, Bitcoin, and Litecoin during a bull market exhibited a random walk (market efficiency) when using a rolling DFA Hurst exponent test. However, when conditions changed and the market entered a bear-market period, we saw signs that the market started to show persistence positive autocorrelation behaviour (market inefficiency).

In addition, we utilised six different tests to investigate market efficiency using a nonrolling fixed period. During the bull- and bear-market periods, the hourly returns of the three cryptocurrencies exhibited market inefficiency.

Similar results could be seen for other financial markets, for example, [Gil-Alana et al. \(2018\)](#) noted that the Baltic stock market rejected the theory of market efficiency during bull- and bear-market states; [Jiang and Li \(2019\)](#) investigated market efficiency for the Chinese, Japanese, and U.S. stock markets, and found market inefficiency in bull- and bear-market states. Furthermore, the Amihud illiquidity ratio illustrated that, in a bear market, hourly Bitcoin returns become more liquid. In contrast, hourly Ethereum and Litecoin returns exhibit less liquidity in this period compared to during a bull-market period.

In addition, we saw that volatility of hourly returns of all three cryptocurrencies decreased during a bear market. There is much scope for future work, and possible extensions could include: (i) focusing not only on hourly, but also higher-frequency data (minutes) due to movement towards higher-frequency cryptocurrency trading; (ii) further investigations into how these results for bull and bear markets could be used for arbitrage or trading strategies, for example, if there is inefficiency in the market during particular periods, if we could use market properties to monitor and predict

when it would be the best time to buy or sell; (iii) investigate how to define bull and bear periods in a high-frequency market. Theoretically, there are many short bull- and bear-market periods within our two subsamples, so this may be more useful if we are considering trading at a higher-frequency level.

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