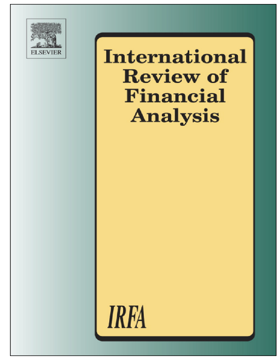
Accepted Manuscript



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PII: S1057-5219(19)30082-1
DOI: https://doi.org/10.1016/j.irfa.2019.05.008
Reference: FINANA 1357

To appear in: *International Review of Financial Analysis*

Received date: 6 February 2019
Revised date: 10 May 2019
Accepted date: 28 May 2019

Please cite this article as: J. Chu, Y. Zhang and S. Chan, The adaptive market hypothesis in the high frequency cryptocurrency market, International Review of Financial Analysis, https://doi.org/10.1016/j.irfa.2019.05.008

The adaptive market hypothesis in the high frequency cryptocurrency market

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The adaptive market hypothesis in the high frequency cryptocurrency market

Abstract

This paper investigates the adaptive market hypothesis (AMH) with respect to the high frequency markets of the two largest cryptocurrencies — Bitcoin and Ethereum, versus the Euro and US Dollar. Our findings are consistent with the AMH and show that the efficiency of the markets varies over time. We also discuss possible news and events which coincide with significant changes in the market efficiency. Furthermore, we analyse the effect of the sentiment of these news and other factors (events) on the market efficiency in the high frequency setting, and provide a simple event analysis to investigate whether specific factors affect the market efficiency/inefficiency. The results show that the sentiment and types of news and events may not be significant factor in determining the efficiency of cryptocurrency markets.

Keywords: Bitcoin, Ethereum, Martingale difference hypothesis, Adaptive market hypothesis, Efficient market hypothesis
JEL: C10

1. Introduction

Cryptocurrencies have emerged as a buzzword in recent years and are currently a hot topic in empirical economic studies. They can be described as digital currencies that use blockchain technology and cryptography to facilitate anonymous and secure transactions. Originally proposed as a cheap, secure, and convenient method to transfer monetary value across the globe, they have developed into something much more than this. One of their interesting properties is that they fall into a specific category of digital currencies known as “decentralised” digital currencies. This means that they are not issued, backed, or controlled by a governing body, such as a central bank or government. These digital currencies have attracted significant attention, not only from the public but also financial institutions, academics, and even world leaders. The values of many cryptocurrencies have seen their fair share of rises and falls, with the current total market capitalisation standing at just over USD $200 billion (November, 2018) (CoinMarketCap, 2018). However, since the peak in the prices of major cryptocurrencies in January 2018, the overall value of the cryptocurrency market has declined significantly by approximately 75%.

The first (and largest) decentralised cryptocurrency ranked by market capitalisation is Bitcoin (BTC), which was initially documented by Satoshi Nakamoto in a 2008 research paper. Nakamoto coined the term 'Bitcoin' and defined it as "a new popular fiat form of currency with an electronic payment system based on cryptographic proof" (Nakamoto, 2009). As a currency, Bitcoin can be traded online 24 hours a day seven days a week. It can be converted into many global currencies for a small fee and it is becoming easier to use it to pay for goods and services online. Moreover, due to the significant volatility in its price, traders and even the public have seen it as an investment opportunity and have rushed towards it in the hope of making a profit.

In comparison, the second largest cryptocurrency known as Ethereum was developed in 2013 by Russian-born Vitalik Buterin. The backbone is a decentralised platform that runs smart contracts – programmable code which can execute certain actions when specified criteria are met. The foundations of the platform itself are not the cryptocurrency (Coindesk, 2016). Instead, the platform is built upon blockchain technology and the Ethereum cryptocurrency (ETH) is the digital currency that is used to run applications and programming code on this platform. Similarly, Ethereum can also be traded and created by users of the platform by contributing their computing power to the validation of transactions and development of the platform.

One of the major research questions relating to cryptocurrencies is whether they should be classed as a currency or a financial asset. There was significant volatility in the price of both Bitcoin and Ethereum in the last quarter of 2017 through to the first quarter of 2018. In addition, there is now an increased awareness of cryptocurrencies among the general public. We believe that this presents an opportunity to contribute to the literature from the perspective of analysing cryptocurrencies as a financial asset that individuals invest in, with the hope of making a financial gain.

Corbet et al. (2018a) conducted a systematic review of cryptocurrency research, since they were first described as a financial asset in 2009, and noted that the related cryptocurrency literature has many gaps. In terms of the research relating to cryptocurrencies as a financial asset, we find that a significant proportion examines the beneficial role of cryptocurrencies in portfolio diversification. For example, Carpenter (2016) showed that Bitcoin appears to be a proper diversification tool which can assist in increasing the return ratios in investment portfolios by using a modified mean-variance model. Brière et al. (2015) used spanning tests and showed that Bitcoin can help to improve the risk-return trading of a well-diversified portfolio. Guesmi et al. (2018) applied multivariate GARCH models to investigate the conditional cross effects, volatility spillover properties, and diversification of Bitcoin across gold and the stock market and reported that Bitcoin can help to reduce the portfolio's risk. Kajtazi and Moro (2019) used a mean-CVaR approach to analyse the implications of incorporating Bitcoin into an optimal portfolio. They concluded that Bitcoin has a positive effect in well-diversified portfolios. Eisl et al. (2015) explored the impact of Bitcoin in well-diversified investment portfolios by applying the conditional Value-at-Risk model and concluded that Bitcoin can be involved in the optimal portfolio process. Platanakis and Urquhart (2018) studied the benefits of incorporating Bitcoin into traditional equity portfolios with eight different asset allocation strategies and various levels of risk aversion. They found that Bitcoin contributes to significantly higher risk-adjusted returns. Henriques and Sadorsky (2018) used three different multivariate GARCH models to investigate the implications of substituting gold for Bitcoin in investment portfolios. They provided evidence that investors may change from gold to Bitcoin for a higher risk-adjusted return.

However, not all of the results are positive. Corbet et al. (2018b) analysed the relationship between three popular cryptocurrencies and numerous other financial assets through both time and frequency domain analysis. Results showed that cryptocurrencies may offer investors some diversification benefits but only over a short trading horizon. Furthermore, the market for cryptocurrencies itself contains its own risks which are difficult to offset. Bouri et al. (2016) examined the safe-haven property of Bitcoin and the return-volatility relating to the price crash in the Bitcoin market during 2013. By applying an asymmetric-GARCH model, they found that Bitcoin may have lost its safe-haven property due to the price crash.

As one of the most essential theories relating to the modelling of financial assets, the efficient market hypothesis (EMH) proposed by Fama (1970) has been studied extensively in the literature. With regards to the underlying information in a financial market, the EMH states that asset prices reflect all available information in the market. Therefore, returns of financial assets should follow a memoryless stochastic process. In other words, the EMH assumes that past price movements have no power in the prediction of future prices and returns of financial assets. There exist three main forms of market efficiency: i) weak form (historical prices); ii) semi-strong form (public information); iii) strong form (all information, including private information). The weak form of the EMH is the one that is most commonly tested to determine whether a market is efficient.

Testing of the weak form of the EMH usually involves testing one of two hypotheses: the random walk hypothesis (RWH) or the martingale difference hypothesis (MDH) (Khuntia and Pattanayak, 2018a). The RWH is directly consistent with the EMH in that it assumes that asset prices resemble a random walk process, thus prices change randomly and cannot be predicted. Similarly, the MDH assumes that the best predictor of a time series given an information set is simply its unconditional mean (Escanciano and Lobato, 2009). In the application to asset prices the implication is that no amount of information would be useful in helping us to make predictions about an asset's price.

Common tests for the RWH relate to the analysis of the autocorrelations of a time series. However, one of the most popular and simplest methods is to analyse the Hurst exponent. The Hurst exponent (denoted by α) gives a measure of the time varying dependence or long memory in a time series. It is commonly computed using the R/S or detrended fluctuation analysis (DFA) methods. The exponent α can take values between zero and one, where a neutral value of $\alpha = 0.5$ suggests that there is no dependence (implying the existence of random walk behaviour). A value of $\alpha < 0.5$ or $\alpha > 0.5$ suggests evidence of anti-dependence or dependence, respectively. For the MDH, there exist a range of tests covering both linear and non-linear dependence. Examples of linear methods include the portmanteau test (Ljung and Box, 1978), variance ratio test (Lo and MacKinlay, 1989), automatic portmanteau test (Escanciano and Lobato, 2009) and the automatic variance ratio (AVR) test (Kim, 2009). Examples of tests for non-linear dependence include the generalised spectral (GS) test (Escanciano and Velasco, 2006) and the consistent test due to Domínguez and Lobato (2003). Further details of the tests can be found in Section 3.

As noted by Khuntia and Pattanayak (2018a), the EMH assumes that the market will always react immediately to any new information making it essentially impossible to 'beat the market' using this information. In other words, the market price fully reflects all available information in the market. Hence, arbitrage opportunities are quickly absorbed by the market and disappear rapidly (Grossman and Stiglitz, 1980). Any opportunity that does arise, which could be advantageous, is assumed to do so by pure chance. The theory states that the market should always revert back to a state of perfect market efficiency. Therefore, the EMH does not allow for any variation in the degree of efficiency over time, or for the efficiency of a market to be influenced by other market factors (Khuntia and Pattanayak, 2018a). However, the theory of no arbitrage (as assumed by the EMH) has been strongly criticised by Grossman and Stiglitz (1980). They state that without such opportunities, there will be no incentive to gather information, and the price-discovery aspect of financial markets will collapse. More importantly, the existence of active liquid financial markets implies that profit opportunities must be present.

In response to this, Lo (2004) proposed a new framework in the form of the adaptive market hypothesis (AMH). This relaxed the main assumption of the EMH to allow for the degree of market efficiency to vary over time. This is arguably more realistic, as a market is unlikely to simply be perfectly efficient or inefficient. Indeed, the development of the AMH suggests considerably more complex market dynamics, which consider that arbitrage opportunities do exist from time to time depending on the environment. Lo (2004) stated that "the EMH and calendar anomalies can co-exist in an intellectually consistent manner when under the AMH", indicating that individuals trade financial assets based on self interest, learn through their mistakes, and this adaptation can lead to competition and innovation in the market. An important implication follows in the AMH where return predictability can arise frequently due to changes in market conditions (Lo, 2004, 2005). Therefore, the AMH suggests that expected return and risk relations vary over time. Thus, by adapting to the evolving market conditions one can achieve a consistent level of expected returns. This is in contrast to the EMH, which suggests that the achievable level of expected returns is dependent on the degree of risk undertaken.

In the literature, many attempts have already been made to study the EMH in the cryptocurrency market. However, the vast majority of the known work has focused on explicitly testing for the weak form of the EMH, including (but not limited to) Urquhart (2016), Nadarajah and Chu (2017), Tiwari et al. (2018), Bariviera (2017), Jiang et al. (2018), and Al-Yahyaee et al. (2018). Few have focused on investigating the AMH. Limited examples include Khuntia and Pattanayak (2018a) who evaluated the daily returns of Bitcoin using the AMH, and Khuntia and Pattanayak (2018b) who evaluated adaptive long memory in the volatility of intra-day bitcoin returns.

It should also be noted that many studies focus on daily cryptocurrency prices and returns as the highest frequency of data. We believe that high frequency data such as hourly prices and returns are becoming increasingly important and should also be studied. Such data has become easier to obtain due to the enormous advances in data processing and collection, and is particularly significant for cyptocurrencies. It was not too long ago when individuals bought and sold cryptocurrencies monthly and weekly – making small profits here and there. However, more recently, many online exchanges have started offering tools and services that allow users to trade cryptocurrencies at a very high speed over the course of minutes and seconds. Therefore, the availability of this data will likely be able to improve the accuracy of volatility measures and forecasts. These may be useful in developing more precise models for price predictions and investment strategies.

In this analysis, we investigate whether there is evidence of the AMH in the markets for the two largest cryptocurrencies – Bitcoin and Ethereum. We implement the consistent and integrated test proposed by Domínguez and Lobato (2003) on high frequency hourly returns to test for the MDH and examine how the efficiency (and predictability) of both markets change over time. Due to the on-going development in cryptocurrencies and their networks, we believe that the efficiency of both markets should vary over time in accordance with these changes. In addition, the market efficiency is hypothesised to show greater variation as we take into account more frequent data.

The main contributions of this paper are: (i) to investigate whether there is evidence of the AMH in the high-frequency (hourly) markets for the two largest cryptocurrencies of Bitcoin and Ethereum, covering both a boom and bust period; (ii) to evaluate the general effect of the sentiment of news and other factors (events) on the market efficiency in a high frequency setting; (iii) provide a simple event analysis to investigate whether specific factors affect the market efficiency/inefficiency. In contrast with Khuntia and Pattanayak (2018a) and Khuntia and Pattanayak (2018b), we utilise high frequency hourly data not just for Bitcoin but also for Ethereum versus the US Dollar and the Euro. In addition, we go a step further in our analysis by not only discussing particular news and events which could influence the market efficiency. We also consider a wider range of news and events and test whether these have a statistically significant influence on the efficiency of the cryptocurrency markets.

The contents of this paper are organised as follows. In Section 2, we describe the high frequency data used in the analysis and provide the summary statistics of the data. Section 3 briefly outlines the consistent and integrated test by Domínguez and Lobato (2003) used to detect linear and non-linear dependence in the data and test for the MDH. In Section 4, we present the main results of the test for dependence and market efficiency. Section 5 attempts to link the variations in the degree of market efficiency to significant events and news and test this. Some concluding remarks are given in Section 6.

2. Data

The data we analyse consists of the historical high frequency hourly prices of Bitcoin and Ethereum versus the Euro (EUR) and US Dollar (USD), respectively, listed on the Kraken cryptocurrency exchange from 11AM on 1st July 2017 to 12AM on 1st September 2018, according to Coordinated Universal Time (UTC). This particular time period was selected to allow us to analyse periods where the prices of the two cryptocurrencies experienced both huge surges (pre–January 2018) and slumps (post–January 2018). The Kraken cryptocurrency exchange was chosen as it is one of the longest-standing cryptocurrency trading platforms – founded in 2011, and it was one of the first exchanges to be listed on Bloomberg Terminal. The data were downloaded from the CryptoDataDownload (2019) website, which sources its data from CryptoCompare (2018), and our analysis is limited to the data available at the time of writing. The cryptocurrencies were chosen based on their ranking in terms of market capitalisation, and ease and availability of purchase. Bitcoin (BTC) and Ethereum (ETH) are considered to be the top two. The combined market capitalisation at the start date of our data was approximately 70% (CryptoCompare, 2018), thus we believe that the data obtained gives a satisfactory representation of the main market players. In addition, the four currency pairs analysed are the four most traded markets on the Kraken exchange (in terms of trading volume). For more details on the two cryptocurrencies, we refer the readers to Chan et al. (2017) and Zhang et al. (2019).

Summary statistics of the hourly log returns of the two cryptocurrencies against the Euro and US Dollar are given in Table 1. The statistics computed include the number of observations (N), minimum, median, maximum, mean, skewness, kurtosis, standard deviation (SD), variance, coefficient of variation (CV), range, and interquartile range. From Table 1, we find that, in general, the BTC/USD returns generate the lowest values of the statistics, whereas the ETH/EUR returns generate the largest values of the statistics. Looking more closely, the ETH/EUR returns give the lowest minimum and largest maximum, however, the BTC/EUR returns give the largest minimum and BTC/USD the smallest maximum. The ETH/EUR and ETH/USD returns jointly give the smallest mean, as opposed to the BTC/EUR and BTC/USD returns which jointly give the largest mean, however, all of the means are small and very close to zero. Note here that the values of 0.00000 are not exactly equal to zero, but rather they only indicate that the first five decimals are zeroes. For all four price series, the corresponding returns are positively skewed, and the kurtosis values are all significantly larger than three. This indicates that the returns are more peaked and heavier tailed than the normal distribution. With respect to the variability of the returns, the ETH/EUR returns generate the largest standard deviation, variance and coefficient of variation. On the other hand, the BTC/USD returns generate the smallest of all these values.

To confirm the properties of the returns as seen in the summary statistics, we test using R (R Development Core Team, 2018) for the presence of normality using the Jarque-Bera (JB) test (Jarque and Bera, 1987) and Kolmogorov-Smirnov (KS) test (Kolmogorov, 1933; Smirnov, 1948), unit root or stationarity using the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), and serial correlation using the Ljung-Box (LB) test (Ljung and Box, 1978). The results for the four sets of log returns are given in Table 1, and we find that the test statistics and results for the four tests on each of the four returns series are significant at the 1% level.

In all cases, the JB and KS tests reject the null hypothesis of normality of the returns data. The ADF test rejects the null hypothesis of the existence of a unit root in the returns (implying stationarity). The LB test rejects the null hypothesis of no serial correlation. Note that for the ADF test, the test statistics correspond to the highest lag for which the test was conducted – these were determined automatically in R and correspond to the lags of 11 in all four tests. The LB test was conducted up to lag 10, and the test statistics were found to be significant at all lags up to and including lag 10.

Statistic	BTC/EUR	ETH/EUR	BTC/USD	ETH/USD
N	10237	10237	10237	10237
Minimum	-0.10363	-0.14394	-0.11145	-0.11546
Median	0.00013	0.00008	0.00003	0.00005
Maximum	0.12934	0.16640	0.11234	0.14187
Mean	0.00010	0.00000	0.00010	0.00000
Skewness	0.29820	0.56361	0.24555	0.49333
Kurtosis	12.52829	14.92791	9.75749	12.19086
SD	0.01165	0.01381	0.01148	0.01363
Variance	0.00014	0.00019	0.00013	0.00018
CV	139.01000	141.36760	138.94410	141.34090
Range	0.23298	0.31034	0.22379	0.25733
IQR	0.00822	0.01055	0.00830	0.01086
Jarque-Bera	67,133*	95,638*	40,734*	63,838*
Kolmogorov-Smirnov	0.47826*	0.47588*	0.47858*	0.47574*
Augmented Dickey-Fuller	-30.3*	-29.2*	-29.9*	-29.1*
Ljung-Box	55.276*	79.740*	40.413*	54.658*

Table 1: Summary statistics of the log returns of Bitcoin (BTC) and Ethereum (ETH), versus the Euro (EUR) and US Dollar (USD), from 12:00 01/07/2017 to 00:00 01/09/2018. Also shown are the test statistics and significance corresponding to tests for normality, stationarity, and serial correlation for the period mentioned. * indicates significance at the 0.01 (1%) level of significance.

3. Method

There exist numerous tests for the MDH, including both linear and non-linear methods. Tests based on linear measures of dependence, such as the Box-Pierce Portmanteau test, variance ratio test, Durbin-Watson test, and sign and rank tests (Escanciano and Lobato, 2009; Charles et al., 2012), are suitable for testing the lack of serial correlation in time series data. However, they are not necessarily the best choice for testing the MDH as some suffer from low power, whilst many are not consistent when only non-linear dependence is present in the data. Furthermore, these tests assume a null hypothesis of an infinite number of autocorrelations being equal to zero, whilst allowing for the presence of dependence beyond second moments (Escanciano and Lobato, 2009). For a survey of tests for dependence, we refer the readers to Charles et al. (2012) and Escanciano and Lobato (2009).

Non-linearity is extremely common in economic data and financial returns, and is present in the cryptocurrency returns computed. In this paper, we test for the MDH in the high frequency cryptocurrency markets of Bitcoin and Ethereum using the consistent and integrated test proposed by Domínguez and Lobato (2003), as in Khuntia and Pattanayak (2018a). As noted by Khuntia and Pattanayak (2018a) and Charles et al. (2012), the DL test shows robustness to factors such as size distributions, non-normality, and heteroskedasticity. Given that the returns of Bitcoin and Ethereum exhibit positive skewness, positive and significant excess kurtosis, evidence of non-normality, and serial correlation, we believe that the DL test would be suitable for our analysis. Furthermore, the DL test is known to be capable of testing for both linear and non-linear dependence, with a null hypothesis of no directional predictability in the data. It also searches for any kind of predictability from specified lagged values of the data (Escanciano and Lobato, 2009).

Let X_t denote the natural logarithm of the hourly prices of Bitcoin and Ethereum versus the Euro and US Dollar at time t, and $Y_t = X_t - X_{t-1}$ be the first difference – in this case, Y_t denotes the one period log returns. The martingale difference hypothesis holds (Escanciano and Lobato, 2009) if

$$\mathrm{E}\left[Y_t | Y_{t-1}, Y_{t-2}, \ldots\right] = \mu. \tag{1}$$

In other words, the best prediction of the price of Bitcoin and Ethereum (versus the fiat currencies) in one hour's time is simply the current price this hour, which implies that the returns of the two cryptocurrencies are unpredictable and follow a martingale difference sequence.

The DL test uses two particular test statistics based on the Cramer-von Mises and Kolmogorov-Smirnov statistics (Khuntia and Pattanayak, 2018a; Escanciano and Lobato, 2009), and are given as

$$\mathrm{CvM}_{n,P} = \frac{1}{\hat{\sigma}^2 n^2} \sum_{j=1}^{n} \left[\sum_{t=1}^{n} \left(Y_t - \bar{Y}\right) \mathbf{1}\left(\tilde{Y}_{t,P} \leq \tilde{Y}_{j,P}\right) \right]^2 \tag{2}$$

and

$$\mathrm{KS}_{n,P} = \max_{1 \leq i \leq n} \left| \frac{1}{\hat{\sigma}\sqrt{n}} \sum_{t=1}^{n} \left(Y_t - \bar{Y}\right) \mathbf{1}\left(\tilde{Y}_{t,P} \leq \tilde{Y}_{i,P}\right) \right|, \tag{3}$$

respectively, where

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{t=1}^{n} \left(Y_t - \bar{Y}\right)^2,$$

$\hat{\sigma}$ is the square root of $\hat{\sigma}^2$, P is a positive integer, $\tilde{Y}_{t,P} = (Y_{t-1}, \ldots, Y_{t-P})'$, and $\mathbf{1}\left(\tilde{Y}_{t,P} \leq \tilde{Y}_{j,P}\right)$ and $\mathbf{1}\left(\tilde{Y}_{t,P} \leq \tilde{Y}_{i,P}\right)$ are indicator functions.

As noted in Escanciano and Lobato (2009), in general, the test statistics and critical values cannot be tabulated. Thus, the asymptotic null distribution can be approximated by using the bootstrap method. After bootstrapping, the corresponding p-values of the tests can be obtained from the (wild) bootstrap distribution, and the null hypothesis of the tests (MDH) can then be rejected if the p-value is less than the specified significance level.

A similar alternative to the DL test is the generalised spectral (GS) test proposed by Escanciano and Velasco (2006). However, we do not consider it in our analysis. One difference with the DL test is that it assumes dependence at all lags (Khuntia and Pattanayak, 2018a), but is still consistent when applied to independent and identically distributed data. However, the GS test is known to be only pairwise consistent, and is inconsistent against pairwise martingale difference sequences which are in fact non-martingale difference sequences (Charles et al., 2012).

4. Results

Since our analysis is focused on the adaptive market hypothesis and how the predictability of the high frequency prices/returns of cryptocurrencies changes over time, we choose not to strictly analyse the period as a whole. Instead, we perform our analysis by using a rolling window of the 168 previous observations (seven days), starting from 8th July 2017, shifting forwards by one observation after each test, and ending on 31st August 2018. P-values are evaluated from the test on each rolling window of data within the period considered. The p-values for the DL test were computed for each of the four sets of returns data generating a total of 10,069 values for each set. It should be noted that the number of p-values is less than that of the returns, due to the rolling window method requiring the previous 168 observations. Thus, we are not able to obtain p-values corresponding to the first 168 hours of each returns series.

Our choice of window size (168 observations) may be considered relatively small. However, there exist analyses in the related literature which have used both slightly larger and also smaller rolling windows. For example, Zhang et al. (2019) use a rolling window of 50 observations to analyse the Hurst exponent for 12 hourly returns of cryptocurrencies using the detrended fluctuation analysis (DFA) method. Ma et al. (2014) also compute the Hurst exponent but in the context of oil and stock market correlations, using a rolling window of 250 observations of daily data. Ma, et al. (2013) use a rolling window of 250 observations of daily data to compute a time varying efficiency index in the context of crude oil and the stock market of emerging economies. Therefore, we believe that our window would be sufficient and large enough to compute the p-values of the DL test and provide an indication of the level of market efficiency.

The p-values for the test on each of the four returns data sets are plotted in Figures 1 (upturn period) and 2 (downturn period). The figures contain two plots each, corresponding to the Euro returns (top) and US Dollar returns (bottom), which show the trend of the p-values covering the whole period analysed from July 2017 to August 2018, inclusive. The p-values for Bitcoin are indicated by the solid red line; the p-values for Ethereum are indicated by the solid blue line; the two black horizontal lines indicate the 0.1 (dotted) and 0.05 (solid) levels of significance. In general, a large p-value close to one indicates that we would fail to reject the null hypothesis of the DL test, suggesting evidence of the MDH and efficiency in the market. A small p-value (less than 0.1 or 0.05) would indicate that there is sufficient evidence to reject the null hypothesis of the DL test (at the 0.1 and 0.05 levels of significance, respectively). This would suggest that the MDH does not hold and there is significant inefficiency in the market.

In general, we find that there are some periods where the overall trends of the p-values in both the Euro and US Dollar plots show some similarities. These are most notable in the months September 2017, and January to May 2018, inclusive. Although in these periods the upwards/downwards movement in the p-values are similar, in other periods the trends are less synchronised. In addition, there are similarities and differences between the trends of the p-values of the series of BTC/ETH versus EUR/USD.

Looking at the plots individually, we find that over the 14 months analysed the p-values are not constant – exhibiting periods of increases and decreases, and very large or very small values. This would seem to suggest that there is evidence of the adaptive market hypothesis in high frequency cryptocurrency prices, as was found in the daily Bitcoin prices in Khuntia and Pattanayak (2018a), and an influence of external factors that lead to the market for Bitcoin and Ethereum becoming more or less efficient over time.

Furthermore, these results are supported by much of the existing literature, for example Bariviera (2017) concluded that Bitcoin was inefficient in its early days but has become increasingly more efficient since 2014 – whilst the level of efficiency has always been fluctuating. Alvarez et al. (2018) found that periods of efficiency and anti-persistence in the Bitcoin market alternate over time. Zhang et al. (2019) analysed high frequency returns of the most popular cryptocurrencies, including Bitcoin and Ethereum, and found evidence that the efficiency of these markets fluctuates over time and does not remain constant. Zhang et al. (2018) state that most cryptocurrencies do not show any particular trends for market efficiency, but Bitcoin does show persistent behaviour prior to 2015, and more random behaviour since 2015. Tiwari et al. (2018) computed an efficiency index to measure the efficiency of Bitcoin prices and found it to vary with time – being relatively efficient with the exception of some periods between 2013 and 2016. Caporale et al. (2018) found that the persistence in the market for four cryptocurrencies evolves over time and does not remain constant. However, there have been instances of contradictory results, for example Brauneis and Mestel (2018) found that for 73 cryptocurrencies the markets are either efficient or inefficient. Jiang et al. (2018) analysed the time varying dependence in the Bitcoin market and found evidence of consistent long range dependence and no tendency towards market efficiency over time. In comparison to the existing literature, our results reveal more significant short run changes in the market efficiency of both Bitcoin and Ethereum, which may be expected due to the use of higher frequency data.

More specifically, in Figures 1 and 2 (for the Euro data) it can be seen that there are short periods (of a few hours) in most months where the p-values for both BTC/EUR and ETH/EUR dip below 0.1 or 0.05, indicating very short run inefficiency and predictability in the prices of both cryptocurrencies versus the Euro. In terms of extended periods of individual inefficiency, for Bitcoin we find these to be at the end of November 2017, end of January and February 2018, the middle of March 2018, and the beginning of April 2018. For Ethereum we find these to be at the end of August 2017, and the end of July 2018/beginning of August 2018. However, there are periods where both Bitcoin and Ethereum versus the Euro are jointly inefficient, such as the end of September 2017, the end of December 2017 into the beginning of January 2018, and the end of April 2018 extending into the beginning of May 2018.

Interestingly, apart from the latter periods mentioned above, there are few instances where the two sets of p-values follow each other closely. For example, the beginning of October 2017, February 2018, the second half of March 2018, the middle of July 2018, and the beginning of August 2018. However, there are many periods where the p-values for Bitcoin and Ethereum show opposite trends, e.g. increasing/decreasing or high/low values, such as the end of August 2017, November 2017, the beginning of December 2017, the second half of January 2018, the first half of March 2018, the beginning and end of April 2018, and the end of May and July 2018.

There are several notable features in Figures 1 and 2, for example at the end of August 2017 the p-values for Ethereum fall below 0.1 for approximately 200 hours (around 8 days) whilst those for Bitcoin remain large and above 0.5. During this time, it appears that the market for ETH/EUR is significantly inefficient whereas the market for BTC/EUR is significantly more efficient. From the middle to the end of September 2017, the p-values of both Ethereum and Bitcoin appear to be large and follow each other closely but suddenly decrease. Those for Bitcoin fall first and then those for Ethereum follow closely and reduce after a short delay. This similar but delayed movement may indicate some factor or event which initially affects the Bitcoin market with the effect transmitting through to the Ethereum market, leading to both markets becoming inefficient. Considering the trends of the two sets of p-values for November 2017 and February 2018, we find that in general they move in opposite directions within both months with a few small differences. Moving through the end of December 2017, the p-values of both Bitcoin and Ethereum are decreasing and appear to be almost identical, whilst falling below 0.05. Both sets of p-values continue to remain below 0.05 into the beginning of January 2018, indicating sustained market inefficiency. The market for ETH/EUR appears to recover first with an increase in its p-values, followed relatively quickly by a similar increase in the p-values for BTC/EUR. In mid-March 2018, BTC/EUR shows an extended period of inefficiency where its p-values suddenly decrease and remain below 0.1 and 0.05, respectively, for approximately 130 hours (5.5 days). The p-values for ETH/EUR remain significantly greater (more efficient) and appear to be unaffected by the BTC/EUR market. At the end of April 2018 and into the beginning of May 2018, both sets of p-values appear to move in sync (albeit with a small delay) as those for Bitcoin fall below 0.05 followed by those for Ethereum shortly after. Moving into May 2018, the p-values of BTC/EUR appear to increase and peak first before being followed by a peak in the p-values for ETH/EUR. Similary, in mid-May 2018, we find that the p-values for both BTC/EUR and ETH/EUR track each other closely and fall below 0.05. However, those for Ethereum remain below 0.05 for an extended period of approximately 120 hours (5 days), whilst those for Bitcoin increase and become significantly greater (above 0.5) after approximately half of this time.

From Figures 1 and 2 (for the US Dollar data), we also see that there are similar short periods in each month where the p-values for both BTC/USD and ETH/USD drop below 0.1 and 0.05. Again, indicating very short run inefficiency and predictability. In comparison with the Euro data, we find that there may be more extended periods of individual efficiency although some of these periods are similar to those found in the Euro data. For example, for Bitcoin these occur at the beginning of November 2017, in the middle of March 2018, and the beginning of April 2018. For Ethereum, these are found at the end of August 2017/beginning of September 2017, the beginning of November 2017 and March 2018, and at the end of July 2018/beginning of August 2018. However, there are numerous periods where Bitcoin and Ethereum versus the US Dollar are jointly inefficient, and these are found to be at the same general time points as those found in the Euro returns.

In contrast with the Euro data, we find that the number of periods where the p-values of Bitcoin and Ethereum versus the US Dollar show similar or opposite movements is smaller. In terms of similar movements, these are found to be throughout most of September 2017; April 2018; May 2018, the second half of December 2017, the middle of February 2018, and the beginning of August 2018. The periods where the p-values show opposite trends are found to be in November 2017, the first half of December 2017, and March 2018.

Again, we find numerous significant features in the plots of the p-values. At the end of August 2017, we see a similar pattern as in the p-values for the Euro returns. Those for Ethereum show a sudden sharp decrease and fall below 0.05 for approximately 200 hours, whilst those for Bitcoin remain significantly higher, highlighting the difference in the efficiency. With the exception of a few days, throughout September 2017 the p-values also track each other remarkably closely. Those for Bitcoin fall sharply at the end of the month to below 0.05 first followed by those for Ethereum, with both p-values indicating inefficiency in the markets for an extended period. In November 2017, for the Euro returns data the p-values for Bitcoin and Ethereum appear to show opposite trends. Here, for the US Dollar returns data the p-values also show this trend. But in the first half of the month those for Ethereum show a sudden decrease to below 0.05 and remain below 0.1 for approximately 150 hours (6.25 days) before increasing, at which point the p-values for Bitcoin decrease sharply and remain below 0.1 for approximately 100 hours (4 days). This almost seems like a delayed response by the BTC/USD market after the effect of an event is felt by the ETC/USD market. From the middle of December 2017 onwards, we again find that the two sets of p-values track each other very closely and show a similar decline in value at the end of the month into January 2018, as in the case for the Euro returns. Throughout the month of March 2018, the p-values for Bitcoin and Ethereum generally move in opposite directions. However, in the first half of the month, we see a similar trend to that in November 2017 where the p-values of Ethereum drop below 0.1 and 0.05 for around 150 hours (6.25 days). Those for Bitcoin remain significantly larger, and then we see a reversal where the p-values for Bitcoin drop below 0.1 and 0.05 for around 300 hours (12.5 days) whilst those for Ethereum increase and become significantly greater. The trends of the p-values of both cryptocurrencies at the end of April 2018 and the beginning of May 2018 are almost identical to those found in the Euro returns data. Those for BTC/USD appear to fall below 0.05 first followed closely by ETH/USD, but interestingly, the p-values for ETH/USD appear to recover and peak first in May 2018.

We can observe some contrast in the occurrence of efficiency and inefficiency in the results between the boom (July 2017 – beginning of January 2018) and bust (beginning of January 2018 – August 2018) periods. During the boom period, we observe Bitcoin and Ethereum exhibiting a greater majority of periods of market efficiency than inefficiency in both currencies. However, during the bust period we see a greater duration of market inefficiency occurring in both cryptocurrencies. This result could be interpreted in the following way. Within the boom periods, the cryptocurrency market had actually grown steadily with investors gradually entering the market, thus leading to an efficient market phenomenon. However, during the bust period the price had consistently decreased throughout the whole period, which may have caused panic and irrational trading by investors leading to a downward spiral in the market prices, hence resulting in a greater occurrence of market inefficiency.

Using the p-values from the tests, we also computed the general market efficiency of the four currency pairs over the whole time period considered. These are given, in Table 2, as ratios of the number of p-values for each currency pair exceeding 0.05/0.1 divided by the total number of p-values for the whole period. For both the 5% and 10% significance levels, we see the same results where the overall level of efficiency is highest for ETH/EUR and lowest for BTC/USD – the difference being slightly greater at the 10% significance level. Indeed, looking only at the Euro pairs, we also find that ETH/EUR shows a greater level of efficiency overall compared with BTC/EUR. However, the results show that there are no significant differences in the overall level of efficiency between the four markets. A drawback of these ratios is that they do not give us an indication of the timing and duration of the periods of market efficiency/inefficiency, unlike the graphical plots in Figures 1 and 2.

Over the whole period analysed, we find only a few periods where the trend in the efficiency/inefficiency of the cryptocurrencies versus both fiat currencies match closely. These are in the middle of March 2018, where Bitcoin appears to be very inefficient but Ethereum is very efficient; the end of April/beginning of May 2018 where there is an extended period of inefficiency in both Bitcoin and Ethereum. This is interesting as it appears to suggest that in these periods there is a very strong influence on the whole market for Bitcoin and Ethereum affecting both the efficiency of prices and returns versus the Euro and US Dollar. However, in other months there may be more regional factors at play which affect the efficiency of more local European/American Bitcoin or Ethereum markets, leading to efficiency/inefficiency in one market but not in the other.

	Efficiency ratio	
Currency pair	10% significance	5% significance
BTC/EUR	88.39%	93.54%
ETH/EUR	90.84%	95.18%
BTC/USD	87.19%	92.56%
ETH/USD	88.53%	94.02%

Table 2: Efficiency ratios (percentage) for each currency pair of Bitcoin and Ethereum versus the Euro and US Dollar, respectively, for the whole time period analysed. Ratios are computed as the number of p-values exceeding 0.05/0.1 (5% and 10% significance levels) divided by the total number of p-values for the whole period.

5. Discussion

Having discussed the results of the DL test for the four returns series, we now turn our attention to trying to pin point just some of the reasons that may be attributed to these periods of efficiency/inefficiency in the respective

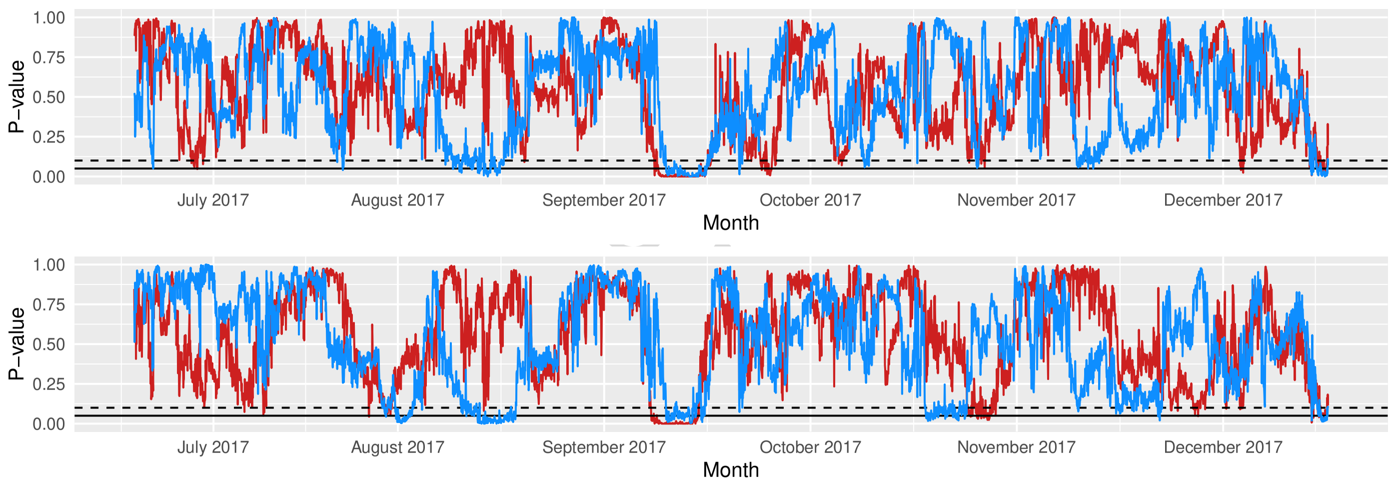

Figure 1: Plot of the p-values (vertical axis) for the Dominguez-Lobato test on the rolling window of returns for Bitcoin (red) and Ethereum (blue) versus the Euro (top) and US Dollar (bottom), for the months of July 2017 to December 2017. The dotted and solid black horizontal lines indicate the 10% and 5% levels of significance, respectively.

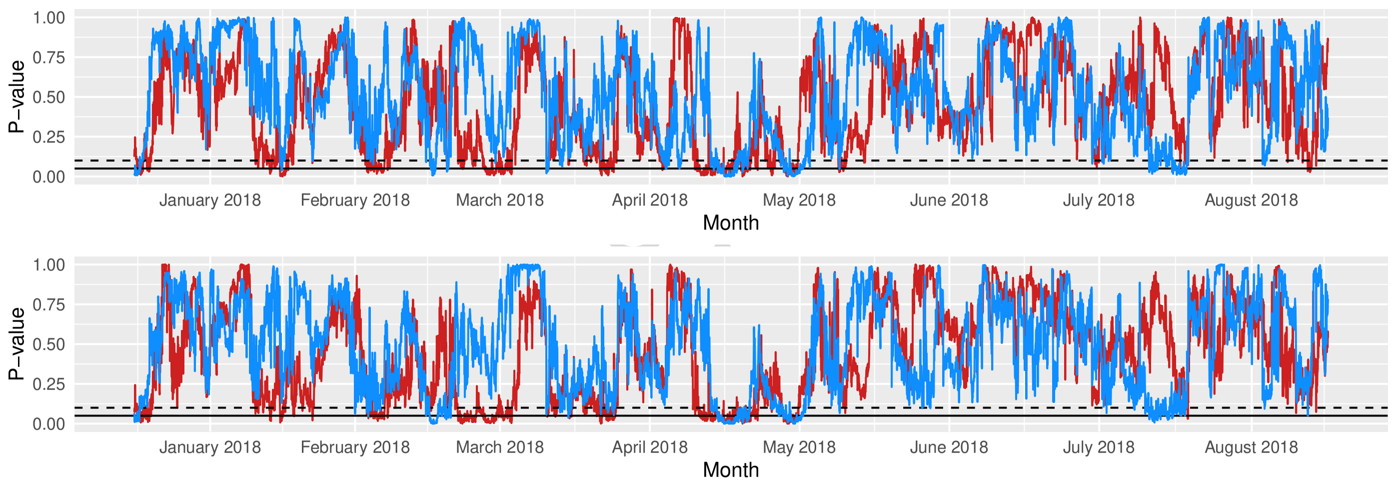

Figure 2: Plot of the p-values (vertical axis) for the Dominguez-Lobato test on the rolling window of returns for Bitcoin (red) and Ethereum (blue) versus the Euro (top) and US Dollar (bottom), for the months of January 2018 to August 2018. The dotted and solid black horizontal lines indicate the 10% and 5% levels of significance, respectively.

markets. We provide a discussion of just some of the news and events occurring mainly in the second half of the time period considered as an example. In early December 2017, the p-values for the BTC/USD returns show a gradual decrease towards 0.1 and 0.05, respectively, in the run up to the first day of Bitcoin futures trading in the US on 11th December 2017 (The Guardian, 2017b). The price of Bitcoin was reported to have been surging, which may have led to increasing predictability in the price as more individuals looked to buy into the market based on the price rises.

Towards the end of December 2017, we see a sudden drop in the p-value for the BTC/USD and ETH/USD returns, indicating increased inefficiency. This could be connected to the temporary suspension of three cryptocurrency exchanges – including Coinbase (one of the largest exchanges), and the suspension of cryptocurrency futures trading (BBC, 2017). Coinciding with this, it was also reported that $64 million worth of cryptcurrencies (approximately 4,700 bitcoins) was stolen from a Slovenian exchange (The Guardian, 2017a). Both of these events may have increased investor uncertainty leading to a significant sell off in the two cryptocurrencies and significant predictability in their prices, but one question that remains is why this effect was not seen in the markets for BTC and ETH versus the Euro?

On a related note, in early January 2018 it was announced that South Korea planned to ban cryptocurrency trading (The Guardian, 2018a). However, it can be seen from Figure 2 that there appeared to be no significant effect on the efficiency of both the US Dollar and Euro markets. This may indicate that the local markets for both Bitcoin and Ethereum, for example American and European, may be more sensitive to local factors and events compared to others.

In February 2018, the sharp rise in the efficiency (and p-values) in Figure 2 could have been due to the announcement from the Chinese government regarding a plan to block all websites related to cryptocurrency trading and initial coin offerings (ICOs) (SCMP, 2018). With a possible restriction in the access to cryptocurrency trading in mainland China, many investors may have turned their attention to investing in major foreign exchanges trading cryptocurrencies in the US Dollar and Euro. This may have led to increased efficiency. During the second half of February 2018, the p-values for BTC versus both the Euro and US Dollar suddenly decrease and the markets appear to become extremely inefficient. Around the 16th and 17th February 2018, a glitch was reported to have occurred in the Zaif exchange in Osaka, which had allegedly opened up the possibility of users purchasing Bitcoin for free, with the total value of bitcoins on the exchange estimated to be worth $20 trillion (Gizmodo, 2018). Again, this significant (but negative) event appears to have contributed to an increase in the inefficiency in the market for Bitcoin, possibly through increased uncertainty in investors leading to some predictability in the price due to the selling of Bitcoin.

As mentioned above, one of the significant periods of extended inefficiency occurs for Bitcoin in the middle of March 2018, which is then followed by an extended period of efficiency in Ethereum. The period of inefficiency in Bitcoin could be due to the run up to the US Securities and Exchange Commission's (SEC) meeting relating to tighter regulation for cryptocurrencies as securities (CNBC, 2018a). Inefficiency may have been pushed further by the head of the International Monetary Fund (IMF), Christine Lagarde, who called for Bitcoin to be controlled using its own blockchain technology due to its possible uses in terrorism and money laundering (The Guardian, 2018b). Furthermore, at this time, Google also announced a ban on advertising for cryptocurrencies and ICOs on its search platforms (Reuters, 2018a), which is likely to have had the same negative effect.

However, this period is then followed by a rapid increase in efficiency in the Bitcoin market, which may be linked to the G20 meeting regarding cryptocurrencies around 20th March 2018. In this meeting, it was reported that cryptocurrencies such as Bitcoin should not be outright banned, with the US Financial Stability Board commenting that cryptocurrencies do not pose a risk to financial stability (CNBC, 2018b). Due to this positive news, the value of Bitcoin rose by over 20% (CNBC, 2018b), which may have contributed to reducing uncertainty and increasing efficiency in the Bitcoin market.

Moving into the beginning of April 2018, there is an extended period of inefficiency in the prices of Bitcoin versus the Euro and US Dollar. During this time, China announced that it was to implement 106 new tariffs on US products, provoking fears of further protectionism and possibly leading to investors moving towards safer investments (CNBC, 2018c). However, one may question whether these two events could be related, and why there was no significant effect on the market efficiency of Bitcoin versus the US Dollar, which may have been expected.

The second of the significant features in Figure 2, the extended period of inefficiency in the prices of both Bitcoin and Ethereum versus the Euro and US Dollar at the end of April 2018, could relate to the infamous cryptocurrency exchange Mt. Gox. Although Mt. Gox suffered a significant hack in 2014 and subsequently went out of business, at the end of April 2018 it suddenly moved 16,000 bitcoins (approximately USD $140 million) from its holdings into an unknown address creating fear and panic among investors of a possible crash in the value (Independent, 2018). It was later revealed that this address belonged to an exchange, which may be the reason why many investors sold Bitcoin (leading to a predictable drop in the price) in anticipation of a massive sell off by Mt.Gox that may later have led to a reduction in the price.

During the end of April 2018, there was some speculation regarding Bitcoin trading inversely with gold (Hacked, 2018). Many had reported that in recent months the price of gold had been steadily declining and that of Bitcoin had been on the rise, with the growth and stabilisation in the Bitcoin market leading to efficiency. If this were a significant factor, then one may expect that the steady decline in the price of gold since April 2018 should correspond with a period of extended efficiency in the Bitcoin market. However, it should be noted that since April 2018 the efficiency of the market for Bitcoin has in fact not been stable.

The continued significant inefficiency in Ethereum into the beginning of May 2018 may have arisen from the investigation by US regulators into the original creation of Ethereum (CNBC, 2018e). They noted that the creation of Ethereum was "probably an illegal securities sale" (CNBC, 2018e), due to the speculation that its creation would lead to a rise in the value of an asset. Furthermore, a hearing by the US SEC and Commodity Futures Trading Commission (CFTC) on Ethereum and Ripple was inconclusive (Coinspeaker, 2018), which was followed by US regulators urging the SEC to confirm whether Ethereum tokens were securities (Bitcoinist, 2018). This constant uncertainty of whether Ethereum should be classed as a security is likely to have sparked fear among investors leading to short term selling and predictability in the price, increasing inefficiency.

Towards the end of May 2018, we can see a recovery in the p-values corresponding to Ethereum versus both the Euro and US Dollar. This rapid increase in the p-values and efficiency are likely to have been influenced by Amazon announcing its move into blockchain, by partnering with a startup which utilises the Ethereum blockchain as its backbone (CNBC, 2018f), and Ethereum being ranked the number one cryptocurrency in the Chinese government's first monthly 'Global Public Chain Assessment Index' (Reuters, 2018b).

Our reasoning for the changes in the efficiency of the Bitcoin and Ethereum markets fall in line with those suggested in Khuntia and Pattanayak (2018a), who also found that variation in the efficiency of the market for Bitcoin corresponded to positive/negative news or events – e.g. positive news appeared to increase the efficiency whilst negative news reduced the efficiency. We note that although this explanation may appear to be simplistic, it does provide the basis for investigation into the causes of the changes in efficiency. Indeed, further reasoning has been proposed by others, such as Brauneis and Mestel (2018) who suggested that the efficiency of cryptocurrency markets was related to liquidity and size, where increased liquidity and increased market capitalisation (as a proxy for size) both corresponded with a more efficient market. Alvarez et al. (2018) found that anti-persistence in the Bitcoin market was cyclical and was linked to the distinct lack of market makers, whilst general variations in the level of efficiency could be attributed to exogenous effects from macroeconomic factors and endogenous effects from Bitcoin being an emerging market. Furthermore, Alvarez et al. (2018) stated that due to the regular affluent price rallies in the Bitcoin market, the idea of perfect market efficiency is not plausible. Jiang et al. (2018) also suggested that inefficiency in the Bitcoin market was due to the "irrational behaviour of investors" and the "lack of a reasonable pricing mechanism".

We have already discussed the fact that the market efficiency for both Bitcoin and Ethereum versus the US Dollar and Euro vary over the time period analysed and over the course of different hourly periods. However, cryptocurrencies present an interesting problem with regards to policy implications due to their decentralised nature. As no central bank or government controls or oversees the networks for Bitcoin and Ethereum, traditional methods of intervention in financial markets, such as adjustments to money supply, quantitative easing, market reforms, buying and selling currency to control the exchange rate, etc. are not directly applicable. On the surface, the market efficiency for cryptocurrencies seems to be affected (amongst other factors) by the uncertainty of its legality and regulation. Or at least events relating to these factors appear to coincide with changes in the level of market efficiency. For example, events such as suspension of trading, and discussions of tighter regulation and the legality of cryptocurrencies appear to be connected with a tendency towards market inefficiency. On the other hand, welcoming the adoption of blockchain and cryptocurrency technology, and discussions about less restrictive regulation appear to be connected with a tendency towards market efficiency. Thus, in the short term, it is unlikely that the efficiency of cryptocurrency markets can be effectively controlled. Until more concrete legislation and regulation is developed for cryptocurrencies, it is likely that the markets will continue to show very rapid changes in efficiency when general discussions about these issues take place without generating a definite outcome. For further discussion on the (monetary) policy implications of cryptocurrencies, we refer the readers to Claeys et al. (2018).

5.1. Event analysis

Whilst we have found many events which appear to correspond with significant changes in the p-values of all four returns series, we perform further analysis to try and link these both formally and statistically. Given our discussion, we hypothesise that positive news or events may lead to an increase in the p-value (more efficient market) whilst negative news or events may lead to a decrease in the p-value (more inefficient market). To conduct this analysis, we looked at all news articles relating to Bitcoin and Ethereum published on the Bloomberg (2019) website. We performed a search on the website, for the time period of the data, using the two cryptocurrency names as keywords. Information gathered included the date and time that the article was published, the sentiment (positive, negative or neutral) of the article, and the category that the news related to: i) exchange rate; ii) trading platform; iii) other cryptocurrencies; iv) regulation; v) investment; vi) politics; vii) cybersecurity; viii) technology. We then cross-referenced the dates and times of the articles and computed the average p-values for the 12 hours before and after each publication time, interpreting the difference between these two values as the change in the average p-value at the corresponding time point.

In the first step, we are interested in whether, on average, positive (negative) news and events had positive (negative) effects on the average p-value. More specifically, does a news article with positive sentiment correspond with an increase in the average p-value calculated 12 hours before and after the publication time (and vice versa)? The results are given in Table 3, where for each of the four returns series we computed four ratios. These were computed by totalling the number of news articles which had positive or negative sentiment and corresponded with a positive or negative change in the average p-value. This was then divided by the total number of positive or negative changes in the average p-value.

The results in Table 3 suggest that, in general, there is no significant link between news and events with positive/negative sentiment leading to a corresponding positive/negative change in the average p-values. We do notice, however, that there are more cases where positive sentiment in news and

Currency pair	Ratios (+) Sentiment (+) Δ p-value	(+) Sentiment (−) Δ p-value	(−) Sentiment (−) Δ p-value	(−) Sentiment (+) Δ p-value
BTC/EUR	0.26	0.25	0.21	0.21
ETH/EUR	0.25	0.20	0.16	0.25
BTC/USD	0.29	0.22	0.23	0.19
ETH/USD	0.25	0.19	0.17	0.25

Table 3: Table of ratios of cases where the average p-value changes were positive/negative and where the sentiment of the news was positive/negative, computed for each of the four currency pair series.

events correspond with positive changes in the average p-values, compared with negative sentiment and negative changes. This is also more apparent for the Ethereum currency pairs compared with the Bitcoin currency pairs.

The second part of the analysis involved performing a simple regression of the change in the average p-value on the information and factors gathered from the news articles. This was to investigate whether any of the specific factors noted were significant determinants of the p-values and thus market efficiency/inefficiency. The regression model used is given by:

$$\begin{aligned}\Delta\text{p-value}_i = \beta_0 &+ \beta_1 Positive_i + \beta_2 Negative_i + \beta_3 Neutral_i + \beta_4 Exchange_i \\ &+ \beta_5 Trading_i + \beta_6 Other_i + \beta_7 Regulation_i + \beta_8 Investment_i \\ &+ \beta_9 Cybersecurity_i + \beta_{10} Technology_i + \varepsilon_i\end{aligned}$$

for $i = 1, \ldots, n$ where n is the sample size, and the independent variables are dummy variables taking a value of zero or one corresponding to the sentiment and category of the news. We performed the regression analysis for the changes in the average p-values corresponding to each of the four currency pairs. Note that the '—' value for the coefficient of 'Neutral' indicates insufficient data for this dummy variable in the regression. The results are presented in Table 4. Overall, based on the regression output, we do not find strong evidence to support the hypothesis that positive (negative) news and events lead to positive (negative) changes between the average p-values before and after the news. From Table 4, we find that the sentiment of news is only significant in the case for the BTC/USD currency pair. Moreover, the only significant effect we find (at the 10% level) is that positive news would increase the change in average p-values for the test on BTC/USD returns. Assuming all else remains equal, this implies that a positive news event would

	Currency pair/Estimated coefficient			
Independent variable	BTC/EUR	ETH/EUR	BTC/USD	ETH/USD
Intercept	−0.16903	0.00605	−0.16651*	0.02197
Positive	0.12393	0.04493	0.17259*	0.01887
Negative	0.13066	0.01636	0.14735	0.01834
Neutral	0.11543	—	0.14810	—
Exchange rate	0.04975**	0.01839	0.02150	−0.00586
Trading platform	0.03886	0.01998	0.02284	0.01267
Other cryptocurrency	−0.00021	−0.04315	−0.00453	−0.04011
Regulation	−0.00669	−0.00916	0.01090	−0.02862
Investment	−0.01031	−0.04992*	−0.01984	−0.03282
Cybersecurity	−0.00088	0.02388	−0.02199	0.01767
Technology	0.05475**	−0.01666	0.00757	−0.00275
R^2-adjusted	0.03137	0.01281	0.00947	−0.04470

Table 4: Table of estimated regression coefficients, computed for the changes in average p-values for each of the four currency pair series. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

lead to an increase in the level of the average p-values immediately after the event. This suggests that positive news relating to Bitcoin would lead to an increase in the efficiency of the BTC/USD market. However, negative and neutral news and events appear to have no significant influence on any market.

Considering the various categories of news and events, we also find limited significant results. For the BTC/USD and ETH/USD currency pairs, the categories of news and events appear to have no explanatory power for the change in the average p-values and market efficiency. For the BTC/EUR currency pair, two factors appear to be positive and significant (at the 5% level of significance), exchange rates and technology. Assuming all else remains equal, this implies that news and events relating to Bitcoin exchange rates or Bitcoin technology would lead to an increase in the level of the average p-values immediately after the event. This suggests that when news relating to these two factors are published, there is likely to be an increase in the efficiency of the BTC/ETH market. The only other significant result that can be found from Table 4 is the effect of investment news for the ETH/EUR currency pair. Investment appears to be a negative and significant factor (at the 10% level). Assuming all else remains equal, this implies that investment news leads to a reduction in the level of the average p-value immediately after the event. This suggests that news relating to investment would lead to an increase in the inefficiency of the market for ETH/EUR. A similar regression was also performed, which included the interaction effects between the sentiment and news categories, however, similar results to those in Table 4 were found and so are not shown here. This appears to suggest that there is no significant link between the sentiment and type of cryptocurrency news and events, and the market efficiency of the four currency pairs considered. Therefore, it is entirely possible that there are other factors or some kind of randomness which influence investor behaviour, and thus the market efficiency.

We should note that this method is certainly not without its faults. For example, subjectivity can play a role as news and events relating to certain factors could be interpreted as being positive, negative, or neutral. Whilst we do not list every decision taken in classifying the sentiment of news articles, we have taken the stance that events restricting the development of the cryptocurrencies should be classed as being negative. One of the main examples is tighter regulation of cryptocurrencies, including an outright ban, taxation, and its legality.

Another drawback is that many pieces of news and events are not reported by major news outlets such as Bloomberg, The Financial Times, Wall Street Journal, etc. Instead, more specialist or niche websites focusing only on blockchain and cryptocurrencies appear to report significantly more. One possible explanation for the results of the regression is that the majority of cryptocurrency traders are not the general public. Therefore, they are more likely to be enthusiasts who search out news and events in order to make decisions relating to the buying and selling of cryptocurrencies. Thus, there may be other news and events which are not reported by larger news outlets which are not accounted for in our analysis.

Finally, whilst performing our news search, we found that there appears to be significantly more news articles reporting about Bitcoin compared with Ethereum. This could be due to Bitcoin being treated primarily as a cryptocurrency, as opposed to Ethereum which is primarily a platform for running decentralised applications but also a cryptocurrency. This is likely to have influenced the results since the number of data points for the regression using Ethereum currency pairs is less than that for Bitcoin.

6. Conclusion

In this paper, we have investigated the adaptive market hypothesis with respect to the markets of the two largest cryptocurrencies – Bitcoin and Ethereum. Whilst the classic efficient market hypothesis has been studied extensively in the cryptocurrency literature, to the best of our knowledge, this is the first time that the adaptive market hypothesis has been analysed for Bitcoin and Ethereum in a high frequency setting.

It should be noted that, unlike the efficient market hypothesis, the adaptive market hypothesis does not have a formal test procedure, although evidence of variations over time in the level of market efficiency and predictability in market prices is usually sufficient to confirm the hypothesis. We tested for evidence of the adaptive market hypothesis (by testing for the martingale difference hypothesis) in the markets for Bitcoin and Ethereum versus the Euro and US Dollar, through their high frequency hourly returns, by using the consistent and integrated test proposed by Domínguez and Lobato (2003).

Conducting the test, we measured the linear and non-linear dependence in the four returns series over a 14 month period from July 2017 to August 2018 inclusive, using a rolling window comprising the previous 168 hours (7 days) of data. Our results of the p-values from the tests over the 14 month period indicate that for all four series of prices and returns, the level of dependence and predictability varies significantly and also within each month. There exist periods where the levels of market efficiency move together or show opposite trends.

The results appear to be consistent with the adaptive market hypothesis, where the efficiency of the markets for Bitcoin and Ethereum do not merely take one of two states – efficient or inefficient, but rather the level of efficiency (or inefficiency) varies over time.

We have provided a discussion of numerous events in the cryptocurrency world which appeared to coincide with significant periods of market efficiency and inefficiency. In addition, we have attempted to link these variations to the varying levels of market efficiency and inefficiency. We formally tested this through an event analysis, however, the results appear to indicate that there is no significant relationship between positive news and events leading to increased market efficiency, or negative news and events leading to increased market inefficiency.

This suggests that the adaptive market hypothesis appears to hold true in the high frequency pricing of cryptocurrencies such as Bitcoin and Ethereum, and that it may be a more suitable characterisation of the market efficiency than the more static efficient market hypothesis. The analysis also reveals that there may be short run changes in the efficiency of cryptocurrency markets which are perhaps masked when considering only, say, daily or weekly data. However, the results of our analysis suggest that the sentiment and type of news and events relating to cryptocurrencies has little or no influence on the market efficiency of Bitcoin and Ethereum.

Future work should focus not only on daily but also higher frequency data due to the movement towards higher frequency trading of cryptocurrencies. The results presented in this paper open up an avenue for further investigations into the efficiency of cryptocurrency markets, for example what other factors influence the market efficiency/inefficiency? Do certain factors lead to shorter or more sustained periods of efficiency? If it is possible to make these more concrete, we may be able to use these as additional inputs in improving the accuracy of models for prices and returns of cryptocurrencies. In addition, being able to predict when a cryptocurrency market may turn inefficient, and thus prices become more predictable, may allow investors to determine the best time to invest in a cryptocurrency.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Acknowledgements

The authors would like to thank the Editor and the reviewers for their careful reading and comments which greatly improved the paper.

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Highlights

- Investigation of the adaptive market hypothesis in the high frequency cryptocurrency markets of Bitcoin and Ethereum versus the Euro and US Dollar.
- Evidence of significant variation in the level of market efficiency over time, suggesting the existence of the adaptive market hypothesis in high frequency cryptocurrency markets.
- Discussion and testing of possible links between market efficiency/inefficiency and positive/negative news and events relating to the respective cryptocurrencies.