ERASMUS UNIVERSITY ROTTERDAM
Erasmus School of Economics

Are cryptocurrency prices efficient?

Abstract – This thesis investigates whether the prices of five different cryptocurrencies (bitcoin, Ripple, Litecoin, Dash, and Monero) are efficient, according to the Efficient Market Hypothesis (EMH). The results of three unit root tests and a runs test show that the price of bitcoin is the only cryptocurrency price to follow a random walk process. These results imply that bitcoin's price is efficient, according to the *weak* form of the EMH. The prices of the other four cryptocurrencies are found to not follow a random walk, and therefore to be not efficient. Furthermore, the event study methodology shows that all five cryptocurrency prices exhibit both overreaction and underreaction during news events. The results of the event study methodology indicate that none of the five cryptocurrencies are efficient in the *semi-strong* form of the EMH.

Key words – cryptocurrency prices, efficient market hypothesis, random walk, event study methodology

Master Thesis Financial Economics
Supervisor: Dr. Ruben Cox

Date final version: 21-10-2018

Brian de Groot 414661

Table of Contents

1. Introduction

With the release of the first version of Bitcoin[1] on 9 January 2009, the world was introduced to the concept of cryptocurrencies as they are known today. Between its release and the time of writing this paragraph, the price of one bitcoin has skyrocketed, with a peak of almost 20.000 US dollars per bitcoin in late December 2017. Having bought a single bitcoin exactly one year ago, May 18th 2017, would have resulted in a profit of 329,55% by now. Ever since the huge increase in the price of bitcoin, over the second half of 2017, Bitcoin, and cryptocurrencies in general, gained tremendous amounts of attention. Global media started to report stories about people investing everything they own into cryptocurrencies, and financial columns started to mention bitcoin's value alongside the usual stock market price changes. With bitcoin's market capitalization surpassing 23 of the 25 constituents of the Dutch AEX index, and other cryptocurrencies following bitcoin in its rise, the future of cryptocurrencies might seem bright. However, bitcoin's price spike at the end of 2017 has, since the start of 2018, been followed by a big crash, loosing over half of its value. Aside from the steep price increases, cryptocurrencies therefore stand out from more ordinary investment options on another point, its volatility. The volatility in the price of bitcoin has been 133% since the start of 2013, to put that in perspective; the volatility of more traditional, non-cryptographic, currencies (like the Japanese Yen, the US dollar or the Euro) falls between 8-12% (Yermack, 2015). Volatility, or variance for that matter, is often used as a proxy for uncertainty in financial literature, so the extreme variance in crypto prices may simply indicate the very high risk cryptocurrencies possess. Governmental institutions around the world have also acknowledged the risks around cryptocurrencies. The Securities and Exchange Commission (SEC) in the United States has, for example, launched a counterfeit website offering investors a new and unique cryptocurrency which will launch in the near future. Everyone who tried to sign up through the website received a warning message from the SEC telling them to be more careful when trying to buy new cryptocurrencies in the future (Robinson, 2018). The Dutch institution 'Autoriteit

[1] Bitcoin with a lowercase "b" refers to the currency bitcoin (BTC), whereas Bitcoin with an uppercase "B" refers to the Bitcoin ecosystem as a whole. This ecosystem includes the transaction network of Bitcoin which is powered by Blockchain technology.

Financiële Markten' (AFM) has also expressed its concerns about cryptocurrencies receiving enormous amounts of money from investors before they actually launch. Additionally, cryptocurrencies as a whole do not receive a uniform legal treatment yet. Apart from uncertainty due to high variance in prices and uncertainty about legal treatment, the current holders of different cryptocurrencies are also a possible cause of instability in the crypto markets. The phenomenon of 'Fear of Missing Out' (FOMO) describes the behavior of investors buying cryptocurrencies without having any clue of what they are buying, for the simple reason that they do not want to see other people get rich of it while missing out themselves. This behavior can obviously be identified as herding behavior, which can fuel a bubble effect. The cryptocurrency community has already identified this behavior itself, and the phenomenon is often used to warn people when a new project seems too good to be true. Furthermore, cryptocurrency traders may be subject to other behavioral biases, like the ones identified by behavioral finance literature in stock markets.

Combing the high volatility, which already implies high risk, with the uncertainty about legal treatment and the possible existence of behavioral biases, the question rises whether it is possible for cryptocurrency prices to be efficient. This thesis takes an extensive look at how the price behavior of a new financial asset, cryptocurrencies, conforms to the Efficient Market Hypothesis. The research question is formulated as follows:

Research question: "*Do cryptocurrency prices move in line with the Efficient Market Hypothesis*?"

The high uncertainty around cryptocurrencies, expressed in the form of the high variance, is a big indication that cryptocurrency prices may not be efficient. However, recently there are also signs that the cryptocurrency market is maturing. Coinbase recently launched Coinbase Index Fund and Coinbase Prime, the first being an index fund tracking all cryptocurrencies Coinbase currently supports, and the latter being a cryptocurrency trading platform for institutions wanting to invest large amounts of money into cryptocurrencies (White, 2018). Furthermore, Intercontinental Exchange (ICE), parent company of the New York Stock Exchange (NYSE), is planning to release a platform for both institutions and consumers to buy, sell, and store digital assets such as bitcoin, called the Bakkt ecosystem, in November 2018. Bloomberg has also reported that multiple young professionals have left their jobs on Wall Street to focus on trading cryptocurrencies, since they are making enough money with trading the digital assets (Marsh, 2018). Another indication that the crypto market is maturing is the fact that since December 2017, bitcoin futures are being sold on the Chicago Board Options Exchange (CBOE) (Cboe Exchange Inc., 2018). In general, a more mature market should contribute to more efficient prices in that market, so these signs can be interpreted as positive for the efficiency of cryptocurrency prices.

The answer to the research question of this thesis is valuable for investors, regulators and risk managers. For investors, it will be very important to know if cryptocurrency prices are efficient or not in order to make good investment decisions. As there is currently no correct or accepted way to fundamentally value cryptocurrencies, investors may want to use technical analysis to decide whether or not to invest in certain cryptocurrencies or at certain points in time. However, technical analysis may turn out to be useless if cryptocurrency prices are actually efficient because this means that prices are unpredictable. On the other side, highly inefficient prices which do not react appropriately to certain news events make it very hard to react to these news events accordingly for the investors themselves. For regulators, the efficiency of prices can help them decide if they want to regulate the actual exchange of cryptocurrencies or if they, for example, just want to prevent fraudulent use of cryptocurrencies. The SEC has already announced that they will oversee the launch of new cryptocurrencies, however, they do not see the cryptocurrencies which are already being traded as securities (Pisani, 2018), as the cryptocurrencies already out there do not meet all four criteria of the Howey Test[2]. This means that the SEC is not going to interfere in

[2] The Howey Test is a test created by the Supreme Court in the US to determine if a transaction between two parties represents an investment contract (FindLaw, n.d.)

the trading process of currently existing cryptocurrencies at this point in time. Lastly, risk managers can use cryptocurrencies to diversify their risk beyond the currently available asset classes. It is however important for them to know how stable cryptocurrencies are as a separate asset class, so the efficiency of the prices in the crypto market can help them decide if they want to use cryptocurrencies to diversify their risk.

2. Theoretical background

In order to assess cryptocurrency prices on their efficiency, the Efficient Market Hypothesis (EMH) is used as the definition of efficiency. The theoretical background explains what the EMH assumes about both efficient prices and price shocks as a reaction to news. Furthermore, the three different forms of market efficiency and the relation between the EMH and the Random Walk Hypothesis (RWH) are explained. The first section of the theoretical background ends with violations of the EMH, which have been documented in previous literature. After discussing more traditional finance aspects in the first part, the second and third section of the theoretical background concentrate more on cryptocurrencies in particular. The second section explains how new cryptocurrencies are being launched and when investors can trade them among each other. The third section summarizes relevant previous literature on cryptocurrencies.

2.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) finds its origins in the 1960s, when academics, especially Eugene Fama (1963, 1965a, 1965b, 1970), Paul Samuelson (1965) and Burton Malkiel (1970), started to build further upon the Random Walk Hypothesis (RWH). Ever since Louis Bachelier brought finance and mathematics together in his thesis in 1900, the consensus about stock market prices was that they followed a random walk. Bachelier's work later resulted in the RWH, which makes two assumptions: (1) successive price changes are independent identically distributed (i.i.d.) random variables, and (2) daily price changes conform to the same probability distribution. If the RWH is found to be true, this means that investors cannot predict the movement of a stock price on day t based on any price movements prior to that day. In other words, stock prices move completely random and do not exhibit any kind of patterns, not in the short-run nor in the long-run.

The idea of the RWH developed further into the idea of efficient capital markets, later to be named the EMH. Fama and Malkiel (1970) define efficient markets as markets in which prices 'fully reflect' all relevant information. The idea is that all information about a company is reflected in that company's stock price, this means that stock prices are always equal to their true fundamental value. If this is the case, it is impossible for investors to make returns above the average market returns, also known as 'beating the market', without taking more risk with their investments. If a market is efficient, according to the definition above, it also means that certain strategies like investing in value-stocks does not yield excess returns over the market returns. The EMH furthermore contradicts the idea of technical analysis, which is the art of identifying certain patterns in stock returns and extrapolating these patterns into the future. Since the EMH states that stock prices are always equal to their fundamental value at any point in time, looking back at previous price levels does not yield any information which is not already incorporated into today's stock price, making technical analysis useless.

Fama and Malkiel (1970) furthermore describe three different forms[3] of the EMH in their paper: *weak* market efficiency, *semi-strong* market efficiency, and *strong* market efficiency. The differences between the three forms of efficiency are in the kind of information incorporated into prices. A market is considered to be efficient in the *weak*-form if prices in that market reflect all past publicly available information, which comes down to historical price information. The *semi-strong* form of the EMH states that prices do not only reflect past information but all public information currently available. This means that the market reacts quickly to new information becoming available and incorporates the new information into the price almost immediately. The price reaction to new information should also be of the right amplitude. If a price change, as a reaction to new information, is of the right amplitude there should be no reverse price change in the following days after the news was released, without new information becoming available again. The *strong* form of the EMH is the form where all relevant information, both publicly and privately available, is incorporated into the prices. This means that in a market which is efficient in the strong form, not even insider information can yield an excess return over the market return, without taking more risk, because this information is already incorporated into the price. All three forms of market

[3] The three different degrees of efficiency were first introduced by Roberts in 1967 (Malkiel, 1989).

efficiency imply that prices in that market follow a random walk, and are therefore unpredictable.

When price data is available statistical analysis can tell if prices in a certain market follow a random walk process. A random walk process has certain statistical characteristics, therefore any time-series can be tested to see if it follows a random walk. A variety of tests, both parametrical and non-parametrical, can be used to see if a time-series process exhibits the characteristics of a random walk. For example, a Dickey-Fuller (DF) test can determine if an autoregressive (AR) time-series process contains a unit root, which is true if the process follows a random walk. The parametric, and non-parametric, tests which can be used to test for a random walk and the implications of these tests will be further explained in the methodology.

2.1.1 Violations of the Efficient Market Hypothesis

Ever since the world of finance has been introduced to the idea of the EMH there have been basically two camps of academics, one of which agrees with the idea of efficient markets, while the other one has found multiple violations of the hypothesis. De Bondt and Thaler (1985) did, for example, find that stocks listed on the NYSE which have been declining in value over the past three to five years outperform stocks which have been increasing over the same time period. This empirical finding is in contrast with an efficient market because the fact that a stock has either been increasing or decreasing in value in recent times does not say anything about the expected performance in the future and should therefore not influence the current stock price. This means that the stock prices that exhibit the pattern described above are mispriced over a longer period of time. De Bondt and Thaler explain the pattern they found by overreaction from investors to both extremely positive or extremely negative news. For example, if the stock price of Ford increases from $20 to $30 after a positive earnings announcement, while the actual increase should have been $5, the stock is overvalued due to overreaction to the positive news. The EMH states that this overvaluation will be corrected immediately by investors who recognize the overvaluation of the stock, these investors will sell or short the stock and therefore the price will go down. However, the empirical findings from De Bondt and Thaler show that the adjustment for the overvaluation takes much longer.

The identification of irrational behavior by investors who have, by theory, always been assumed to be rational, created a branch within economic literature. This new branch is now referred to as behavioral finance, which combines economic theory with psychological studies. Behavioral finance argues that in some cases stock prices can deviate from their fundamental value, even for a longer period of time. Overreaction is one of the biases that has been discovered in stock returns and is part of the empirical findings in behavioral finance. However, over the years a lot of investor behavior has been identified which cannot be explained by traditional economic theory. Barberis and Thaler (2003) have summarized most of the empirically found irregularities in their paper called "*A Survey of Behavioral Finance*". Barberis and Thaler also explain how certain behavioral biases can explain the irregularities which have been found. Apart from the irregularities described by Barberis and Thaler, there are also more easily identifiable violations of the EMH. For example, if prices in a market are efficient it is impossible for a bubble to manifest itself, however, multiple bubbles have identified in the past, with most recently the IT bubble around the beginning of the 21st century. The violations of the EMH which have been documented in previous literature do not imply that the EMH is incorrect. Different markets can have different levels of efficiency over different time periods. This means that empirically testing prices to see if they are efficient will always be interesting.

2.2 Initial Coin Offerings

Underlying Bitcoin's subjective success so far lays the technology on which the cryptocurrency runs: Blockchain. Blockchain technology has since its initiation created a path for a lot of other cryptocurrencies beside Bitcoin, both similar to and different from the currently biggest cryptocurrency. Almost every week new cryptocurrencies are being launched, some of which disappear even before they make it to a big exchange, while others manifest themselves in the top one hundred cryptocurrencies, based on market capitalization, rather quickly. The launch of a new cryptocurrency happens during an Initial Coin Offering (ICO). As the name already implies, this process is quite similar to an Initial Public Offering (IPO), during which stocks of a company get offered to the public for the first time.

In most cases, a team of developers comes up with an idea for a new cryptocurrency and they create a mining process to generate coins of this new currency. The first step is the release of a website with information on the new currency and the team behind it. The functioning and mining process of a new cryptocurrency is usually explained in a so-called white paper, which can be found on the official website of the currency. Interested investors can sign up to participate in the ICO, in order to be one of the first to buy the new coins. When buying a cryptocurrency during an ICO, the coins are bought directly from the developers of the cryptocurrency. Investors who participate in ICO's obviously hope to make a profit on the bought currencies once they start to trade on an exchange. Usually, an ICO follows different stages in selling all the available coins, once all coins are sold the development team will try to get their cryptocurrency listed on an exchange, where investors can then exchange the currency for all other available cryptocurrencies on that exchange.

2.3 Literature Review

This section summarizes the available literature on cryptocurrencies relevant to this thesis. Most of the previously conducted work focusses on Bitcoin, however Bitcoin shares almost all of its characteristics with all other cryptocurrencies. The empirical findings from previous literature have been divided into: (1) findings which (positively influence) could potentially enhance price efficiency, and (2) findings which (negatively influence) could potentially decrease price efficiency for cryptocurrencies.

2.3.1 Inefficient Cryptocurrency Prices

Kristoufek (2013) looks at both the number of page views on Wikipedia, and the search query on Google Trends for the word 'Bitcoin[4]', and combines the two to measure the interest in Bitcoin. His findings show that an increase in the interest for Bitcoin has a positive effect on the price of bitcoin when the current price is above average. If bitcoin's price is below average, an increase in interest has a negative effect on the price. Both the positive and negative relationship between the interest in Bitcoin and its price are signs of herding behavior. Herding behavior creates an overreaction to either an upwards or downwards trend, this obviously makes prices more inefficient. As the author also mentions this behavior can create an environment suitable for the creation of a bubble, which also violates the EMH.

Barber, Boyen, Shi, and Uzun (2012) list several reasons why Bitcoin has been a success so far, contrary to previously introduced cryptographic money. The authors agree with Satoshi Nakamoto (2008), alleged inventor of Bitcoin, that the decentral character of Bitcoin is very important because users do not need to trust a third party with their money. However, the authors also identify a critical point of Bitcoin, the fixed money supply of 21 million coins. Other researchers (Grinberg, 2012; Yermack, 2015) have also pointed towards the fixed money supply as a big potential problem for Bitcoin in the long-run. The fixed number of minable coins poses the problem of a deflationary spiral. The authors explain that the only way of grow, once the total supply is reached, for bitcoin is through appreciation, however, when there are no more bitcoins to be mined the incentive to participate in the network decreases drastically. The authors believe that the incentives of miners, or anyone participating in the Bitcoin ecosystem, is crucial to the survival of Bitcoin. This is also the conclusion of Grinberg (2012) who believes that panic, for any reason, among users of Bitcoin will lead to a sell-off and eventually to the end of Bitcoin. Kroll, Davey, and Felten (2013) conclude their paper in line with both Grinberg and Barber et al., stating that the sustainability of Bitcoin is purely based on the consensus of the users of the ecosystem. Both the fixed supply of coins and the dependency on the consensus of users pose problems for efficient

[4] The search term used in this research is insensitive to the use of upper- or lowercase letters.

cryptocurrency prices. In stock prices, a seasoned equity offering (SEO) is the offering of new shares by a company whose shares are already being traded on an exchange. This process is an event which is announced in advance and obviously affects the current stock price. For Bitcoin, the information on how many new coins are being mined each day is not readily available. Furthermore, the mining process is an ongoing process without any notifications towards investors. This makes it difficult for investors to incorporate the mining of new coins into the current price of bitcoin, making it harder for prices to be efficient. Beside the fixed amount of coins, the influence investors' consensus can have on bitcoin also makes it difficult for prices to be efficient. If investors do in fact portray herding behavior, and big sell-offs happen without a proper reason, prices will inevitably not be efficient.

Catania and Grassi (2017) model the financial times series of 289 different cryptocurrencies, focusing mostly on Bitcoin, Ethereum, Ripple, and Litecoin. The authors want to identify the change in volatility after both positive and negative price shocks. They find a greater increase in volatility after a negative price change than after a positive price change. This result indicates that investors react stronger to a decrease in the price than to an increase, regardless of the importance of the reason for the price change. This behavior can possibly be explained by loss aversion, which states that investors would rather miss out on an opportunity to make a five dollar profit than to actually lose five dollars. Being it due to loss aversion or not, the asymmetric reaction of investors to price changes will make it hard for cryptocurrency prices to be efficient.

Finally, Badev and Chen (2014) find that exchange rates for bitcoin are not well aligned, the gap in the fraction of a bitcoin which can be bought with 100 US dollars and with a 100 US dollar equivalent in a different currency is too big. The authors argue that this finding is not a result of unexploited arbitrage opportunities, but rather a lack of depth in the exchange markets for bitcoins. The authors do not take the possibility into account that the problem could be a result of imprecise exchanges rates between ordinary currencies. However, the more likely case that the problem originates from the exchange rate of bitcoin is a clear sign of inefficient pricing among cryptocurrencies.

2.3.2 Efficient Cryptocurrency Prices

Badev and Chen (2014) also investigate the number of users per day and the value of daily transactions for bitcoin. The authors use publicly available transaction data as well as data provided by Satoshi Dice, a large online gambling service where users can pay with bitcoins. The authors find that the number of users of Bitcoin doubled every eight months between 2011 and 2014, this finding is based on a consolidated number of addresses used. The rapid increase in user can potentially increase the price of bitcoin significantly. Besides the empirical findings by Badev and Chen, it seems clear that the attention towards cryptocurrencies has recently increased exponentially. As Storms, Kapraun, and Rudolf (2015) find that investor attention positively affects the efficiency of the price of a stock. It is possible that this same effect holds for cryptocurrencies and therefore that the efficiency in prices has increased alongside the increase in attention.

Hayes (2017) uses data from the 66 most widely used cryptocurrencies to try to explain the cross-section price differences between the different currencies. In his research, Hayes regresses a set of possible explanatory variables on the natural logarithm of the price of the different coins. He finds that the needed computer power to mine a certain cryptocurrency has a positive effect on its price. Following this result he also finds that the rate of unit production is negatively related to the price of a cryptocurrency, in other words, the more coins mined per minute, the lower the price will be. This finding shows that investors may actually know about the amount of mined coins per day and incorporate this information into the price. Based on his findings, Hayes creates a cost of production valuation model for cryptocurrencies, his model is capable of making a close approximation of the price of bitcoin in US dollars. The model implies that all factors influencing the cost price of a certain cryptocurrency affect its price. So for example, if the worldwide price of electricity decreases, the cost of production for cryptocurrencies decreases and so will the price of cryptocurrencies. The fact that the model can approximate the price of bitcoin indicates that the price actually includes information on the cost of production. This result is positive with regards to efficient prices, as it seems that prices do incorporate crucial information which may not be readily available to all investors.

2.5 Hypothesis development

The EMH states that prices are efficient if they reflect all relevant information. Empirical findings can be addressed both in favor of and against the possibility of efficient cryptocurrency prices. In this section, the research question, as stated in the introduction, is substantiated by four hypotheses. Answering these hypotheses first will lead towards an answer to the research question.

As mentioned in the introduction, the cryptocurrency market seems to be maturing, and certain empirical findings from previous literature can be seen as contributors to efficient prices among cryptocurrencies. However, the cryptocurrency market and its investors are still very young, especially when compared to stock or foreign exchange (FX) markets. For example, the first FX futures market launched in May 1972 (Brodsky, 1974), whereas the first cryptocurrency futures market was initiated in December 2017. And even in the more mature markets, like the stock and FX markets, there are still empirical findings contradicting the efficiency of those markets. It is therefore very much possible that the current market is still vigorously influenced by sentiment-driven investors, possibly due to their lack of understanding and experience. The first hypothesis therefore states the following:

Hypothesis 1: The prices of cryptocurrencies follow stationary processes and are therefore inefficient, according to the *weak* form of the EMH.

Furthermore, due to the, hypothesized, inefficient prices, the absolute daily price changes of the different cryptocurrencies will not be random, leading to the second hypothesis:

Hypothesis 2: The absolute daily price changes of the cryptocurrency prices are non-random.

As previous literature has shown (Barber et al., 2012; Grinberg, 2012; Kroll, Davey, and Felten, 2013) the future of cryptocurrencies is closely related to the overall consensus of the users of the currencies, and the starts of a big sell-off can potentially lead to the end of a cryptocurrency. If the prices of cryptocurrencies are in fact heavily influenced by the overall consensus among the users, and the same users exhibit herding behavior by following others during a sell-off, this creates an environment prone to both overreaction and underreaction.

Hypothesis 3: Cryptocurrency prices show clear signs of both overreaction and underreaction to news events, implying that the prices are not efficient in the *semi-strong* for of the EMH.

The asymmetric reaction to price changes documented by Catania and Grassi (2017) indicate that cryptocurrency investors might be loss averse. If this is in fact the case the overreaction during negative events is bigger, in absolute value, than the overreaction during positive events. Furthermore, it is then expected that the frequency of overreaction documented during news events is higher among the negative events.

Hypothesis 4: The frequency of overreaction documented among negative events is higher than the frequency of overreaction documented among positive events.

Hypothesis 5: Cryptocurrency prices will showcase greater overreaction when negative news is released, than when positive news is released.

3. Data

According to CoinMarketCap (CoinMarketCap, n.d.) the current, as of 28 September 2018, number of different cryptocurrencies out there right now, is 2008. The different coins are being traded at 14,269 different exchanges, ranking up a total market capitalization of over 220 billion US dollars. The data used in this thesis consists of the daily prices of five different cryptocurrencies: bitcoin (BTC), Ripple (XRP), Litecoin (LTC), Dash (DASH) and Monero (XRM). The choice for these five currencies is first off based on market capitalization, after ranking all cryptocurrencies on market capitalization the five currencies with the most overlapping available data have been selected. The dataset contains daily prices for all five cryptocurrencies ranging from May 21 2014 till 1 July 2018. The daily prices have been collected from CoinMarketCap. The prices on CoinMarketCap are the volume weighted averages of the prices reported on all available exchanges. The data from CoinMarketCap includes the following daily values: highest price, lowest price, opening price, and closing price. For comparison purposes, Thomson Reuters DataStream is used to obtain daily price data for the S&P500 index over the same time period. The crypto prices used to make calculations in this thesis are the daily closing prices, the reason for this is DataStream's definition of equity prices: "*Datatype (P) represents the official closing price. This is the default datatype for all equities and ETF's",* this way there is a consistent use of prices throughout this thesis. The closing prices of cryptocurrencies are used to calculate daily returns for all five coins. None of the daily return observations have been removed, even though some can be identified as outliers by certain rules of thumb, such as two times the standard deviation from the mean for example. However, the very extreme daily changes in the prices of cryptocurrencies are not uncommon and are actually very interesting when looking at the efficiency of prices.

All five cryptocurrencies are introduced shortly, explaining the purposes of the different coins. After the introduction of the cryptocurrency, the performance of the coin over the sample period is being measured in multiple ways. Table 1-5 show the *buy-and-hold* returns, the lowest daily returns, the highest daily returns, the average daily returns, the annualized volatility, a Sharpe Ratio, and a reference Sharpe Ratio for each cryptocurrency. All performance measures are being calculated per calendar year, as well as for the whole sample period. The daily returns in 2014 range from May 22 till December 31 and the daily returns in 2018 range from January 1 till July 1, all other years include daily returns for the full calendar year.

Tables 1-5 include Sharpe Ratios for all five cryptocurrencies. Usually, the Sharpe Ratio is used to compare different investment opportunities, often used by Mutual Funds (MFs) and Exchange Traded Funds (ETFs), with a higher ratio indicating a better performance. The original Sharpe Ratio is defined by the following equation (Sharpe, 1994):

$$S_h = (R_{Ft} - R_{Bt}) / \sigma_{RFt} \tag{1}$$

Where R_{Ft} are the returns on a certain fund you want to assess and R_{Bt} are the returns on a benchmark portfolio. Usually, the benchmark used to calculate the Sharpe Ratio is a virtually risk-free object, like short-term government bonds. This way the Sharpe Ratio shows how a certain fund or index performed, compared to a risk-free investment. The Sharpe Ratio furthermore corrects the returns for its volatility, by dividing the 'excess returns' ($R_{Ft} - R_{Bt}$) by the volatility of R_{Ft}. The Sharpe Ratios displayed in Table 1-5 are defined by the following equation:

$$Sharpe\ Ratio = (R_i - R_{S\&P500}) / \sigma_i \tag{2}$$

Where R_i are the returns on the respective cryptocurrencies, $R_{S\&P500}$ are the returns on the Standard & Poor's 500 Index (S&P500) over the same time period, and σ_i is the volatility in the daily returns of the different coins. All Sharpe Ratios are annualized using the daily returns of the reported year. The idea behind calculating this Sharpe Ratio is that it compares a traditional, relatively low-risk investment, with a new high-risk investment; cryptocurrencies. Therefore, the Sharpe Ratios in Table 1-5 display how the choice to invest in cryptocurrencies, rather than in the S&P500, would have paid off, while also correcting for the volatility of the different cryptocurrencies. To give more meaning to the reported

Sharpe Ratios, table 1-5 also include a reference Sharpe Ratio. This reference Sharpe Ratio is the Sharpe Ratio of the S&P500 compared to a fictitious risk-free rate of 1%. The meaning of this reference ratio is therefore how the S&P500 performed compared to a risk-free investment object which yields 1% of return each year.

3.1 Bitcoin

On October 31 2008 a paper called *"Bitcoin: A Peer-to-Peer Electronic Cash System"*, was published through a mailing list. The paper is allegedly written by someone called Satoshi Nakamoto, however, this name is only known to be an online alias which disappeared a couple of years after the publication of the paper. The paper describes the big advantages Bitcoin has over traditional currencies like the Euro or the US Dollar, with the most important one being the fact that there is no need for a third party to participate in the transaction of bitcoins. Two parties can directly send each other a specified amount of the currency, these transactions are then verified by so-called 'miners'. The validation process by miners eliminates the need for a third party such as a bank. This decentralized approach is to many supporters of the Bitcoin ecosystem the ultimate advantage over traditional currencies.

Performance of Bitcoin (BTC)

Buy-and-hold returns		*Lowest Daily Returns*		*Highest Daily Returns*		*Average Daily Returns*	
2014	-34.89%	2014	-8.52%	2014	15.19%	2014	-0.15%
2015	37.02%	2015	-21.15%	2015	17.82%	2015	0.15%
2016	121.89%	2016	-15.33%	2016	11.95%	2016	0.25%
2017	1318.01%	2017	-18.74%	2017	25.25%	2017	0.86%
2018	-53.24%	2018	-16.86%	2018	13.22%	2018	-0.31%
Full sample	1198.54%	Lowest (2015)	-21.15%	Highest (2017)	25.25%	Full sample	0.25%

Annualized Volatility		*Sharpe Ratio*		*Reference Sharpe Ratio (S&P500)*	
2014	56.69%	2014	-1.20	2014	0.99
2015	68,79%	2015	0.78	2015	-0.03
2016	48.02%	2016	1.71	2016	0.58
2017	95.37%	2017	3.11	2017	2.15
2018	94.76%	2018	-1.25	2018	0.19
Full sample	74.37%	Full sample	1.08	Full sample	0.58

Number of daily returns: 1502

Table 1: Buy-and-hold returns, lowest daily returns, highest daily returns, average daily returns, annualized volatility, Sharpe Ratio, and a reference Sharpe Ratio for each different calendar year as well as for the full sample for bitcoin's daily price data.

Table 1 shows the extremely high buy-and-hold returns for bitcoin, as well as its extremely high volatility. The interesting part about the performance of bitcoin is that, even when considering the high volatility, the performance of the cryptocurrency over 2017 is incredible. This is indicated by the Sharpe Ratio of 3.11, which is quite a bit higher than the likewise impressive Sharpe Ratio of the S&P500 over the same year. Furthermore, table 1 shows the poor performance of bitcoin over the last seven months of 2014 and the first seven of 2018. This indicates that bitcoin's performance has not been incredible.

3.2 Ripple

Ripple created the cryptocurrency with, currently, the third largest market capitalization of all cryptocurrencies: XRP (Ripple). The cryptocurrency shares its name with the company that created it, however, there is a clear distinction to be made. The company Ripple focusses on banks handling international payments, offering an alternative to the usage of SWIFT-codes when processing international money transfers. The alternative Ripple offers is called 'Ripple xCurrent Software', which uses the InterLedger Protocol (ILP). The idea behind this software is that banks can keep using their current digital ledgers, and customers can for example send US dollars to Japan, which the software exchanges to Japanese Yens at a minimal exchange cost. Banks using this software are not at all forced to also use the currency Ripple. In 2016 Ripple introduced its own currency, which is very different from most other cryptocurrencies, as Ripple is not a fully decentralized currency. The company Ripple oversees all XRP transfers and therefore operates as a central bank in RippleNet, which is the network all transfers go through. One of the strongest points of RippleNet is its scalability, the network is capable of settling a transaction in 4 seconds and currently handles around 1500 transactions per second. Ripple states that their network can easily handle the same amount of transactions as Visa, which currently handles over 50.000 transactions per second (Ripple, n.d.).

Performance of Ripple (XRP)							
Buy-and-hold returns		*Lowest Daily Returns*		*Highest Daily Returns*		*Average Daily Returns*	
2014	266.44%	2014	-40.13%	2014	29.09%	2014	0.83%
2015	-75.24%	2015	-15.11%	2015	25.80%	2015	-0.28%
2016	8.30%	2016	-10.32%	2016	39.29%	2016	0.08%
2017	36018.09%	2017	-46.00%	2017	179.37%	2017	2.35%
2018	-80.70%	2018	-29.76%	2018	25.40%	2018	-0.60%
Full sample	6817.96%	Lowest (2017)	-46.00%	Highest (2017)	179.37%	Full sample	0.57%
Annualized Volatility		*Sharpe Ratio*		*Reference Sharpe Ratio (S&P500)*			
2014	133.62%	2014	2.17	2014	0.99		
2015	86.76%	2015	-1.19	2015	-0.03		
2016	71.36%	2016	0.28	2016	0.58		
2017	274.69%	2017	3.05	2017	2.15		
2018	140.61%	2018	-1.60	2018	0.19		
Full sample	163.80%	Full sample	1.22	Full sample	0.58		
Number of daily returns: 1502							

Table 2: Buy-and-hold returns, lowest daily returns, highest daily returns, average daily returns, annualized volatility, Sharpe Ratio, and a reference Sharpe Ratio for each different calendar year as well as for the full sample for Ripple's daily price data.

Table 2 shows the performance of Ripple and the numbers are even more extreme than those of bitcoin, with the absurd *buy-and-hold* returns over 2017 of over 36 thousand percent. Also, where bitcoin lost over 30% of its value over the last eight months of 2014, Ripple's price increased by a factor of over 2.5. However, Ripple showcases the highest annualized volatility over the full sample, compared to the other four cryptocurrencies in this thesis. Besides that, Ripple is also the only cryptocurrency to lose value over 2015 and the biggest loser in 2018 so far. Similarly to bitcoin, Ripple's Sharpe Ratio over 2017 is not affected too much by its high volatility though, producing a Sharpe Ratio of 3.05.

3.3 Litecoin

Litecoin was published on October 13, 2001, by former Google-employee Charlie Lee. The cryptocurrency is very similar to Bitcoin as it is based on the same software, Bitcoin and Litecoin therefore share their decentral attribute. The idea behind Litecoin is to improve on one of the problems Bitcoin faces: transaction costs. Bitcoin's software is altered in some fundamental aspects in order to greatly improve the speeds and costs of a transaction of litecoins, as opposed to the transaction of bitcoins. According to the website of Litecoin (Litecoin, n.d.) the cryptocurrency is complementary to Bitcoin, so it is not a direct rival of the biggest cryptocurrency.

Performance of Litecoin (LTC)							
Buy-and-hold returns		*Lowest Daily Returns*		*Highest Daily Returns*		*Average Daily Returns*	
2014	-74.32%	2014	-14.32%	2014	25.88%	2014	-0.52%
2015	28.89%	2015	-40.19%	2015	42.57%	2015	0.26%
2016	23.36%	2016	-18.88%	2016	25.61%	2016	0.10%
2017	5046.34%	2017	-32.64%	2017	66.59%	2017	1.44%
2018	-64.97%	2018	-19.09%	2018	33.73%	2018	-0.38%
Full sample	657.70%	Lowest (2015)	-40.19%	Highest (2017)	66.59%	Full sample	0.32%
Annualized Volatility		*Sharpe Ratio*		*Reference Sharpe Ratio (S&P500)*			
2014	81.27%	2014	-2.49	2014	0.99		
2015	120.33%	2015	0.80	2015	-0.03		
2016	57.42%	2016	0.49	2016	0.58		
2017	166.06%	2017	3.05	2017	2.15		
2018	123.20%	2018	-1.16	2018	0.19		
Full sample	118.263%	Full sample	0.89	Full sample	0.58		
Number of daily returns: 1502							

Table 3: Buy-and-hold returns, lowest daily returns, highest daily returns, average daily returns, annualized volatility, Sharpe Ratio, and a reference Sharpe Ratio for each different calendar year as well as for the full sample for Litecoin's daily price data.

The overall performance of Litecoin, as shown in Table 3, is quite similar to the performance of bitcoin. Similarly to bitcoin, Litecoin's value only decreases in the last eight months of 2014 and the first eight of 2018. As Litecoin runs on the exact same software as bitcoin, the resemblance in performance is not unexpected. The Sharpe Ratio of Litecoin over the full sample is however substantially lower than the one of bitcoin. The difference in the Sharpe Ratios can easily be attributed to the higher volatility in the daily returns of Litecoin, especially over 2015, and the lower overall *buy-and-hold* returns.

3.4 Dash

Dash, a portmanteau of Digital Cash, is, similarly to Litecoin, a Bitcoin-fork, which means that the cryptocurrency runs on a modified version of Bitcoin's software. Two additions Dash offers to Bitcoin are InstaSend and PrivateSend. As the name already suggests InstaSend allows Dash users to send the currency to someone else instantaneously. InstaSend works due to a second-layer of masternodes which Dash uses, this system verifies and 'locks' transactions immediately to prevent double spending, only after a transaction went through this second-layer it gets verified in the Blockchain ledgers. PrivateSend allows Dash users to make transactions, on the same masternode network used for InstaSend, without revealing their wallet addresses to any of the other users of the network. On its website (Dash, n.d.) Dash calls itself on of the world's first successful decentralized autonomous organizations (DAO).

Performance of Dash (DASH)

Buy-and-hold returns		*Lowest Daily Returns*		*Highest Daily Returns*		*Average Daily Returns*	
2014	-75.34%	2014	-34.75%	2014	115.58%	2014	-0.03%
2015	68.56%	2015	-20.00%	2015	30.23%	2015	0.29%
2016	231.66%	2016	-15.10%	2016	27.25%%	2016	0.44%
2017	9264.92%	2017	-21.59%	2017	54.92%	2017	1.56%
2018	-77.64%	2018	-19.12%	2018	17.07%	2018	-0.62%
Full sample	2849.94%	Lowest (2014)	-34.75%	Highest (2014)	115.58%	Full sample	0.477%

Annualized Volatility		*Sharpe Ratio*		*Reference Sharpe Ratio (S&P500)*	
2014	230.06%	2014	-0.10	2014	0.99
2015	108.68%	2015	0.98	2015	-0.03
2016	86.69%	2016	1.72	2016	0.58
2017	155.85%	2017	3.53	2017	2.15
2018	119.35%	2018	-1.94	2018	0.19
Full sample	142.61%	Full sample	1.15	Full sample	0.58

Number of daily returns: 1502

Table 4: Buy-and-hold returns, lowest daily returns, highest daily returns, average daily returns, annualized volatility, Sharpe Ratio, and a reference Sharpe Ratio for each different calendar year as well as for the full sample for Dash' daily price data.

The performance of Dash does, like the performance of Litecoin, not differ too much from the performance of bitcoin. The *buy-and-hold* returns are however even more impressive than those of bitcoin, especially the substantial price increase over 2017. The high returns on Dash lead to the highest reported Sharpe Ratio of all ratios shown in table 1-5; 3.53.

3.5 Monero

Monero is one of the first, and the most well-known cryptocurrency to run on CryptoNote technology. CryptoNote technology allows for the creation of completely anonymous cryptocurrencies. Where transactions of bitcoins and litecoins are openly verifiable and traceable in the public blockchain ledgers, cryptocurrencies created with the CryptoNote technology work anonymously. Monero argues that wallet addresses of bitcoin users can be linked to real-world users, which tackles the idea of a decentralized cryptocurrency, since people can still see what you are receiving and sending (Monero, n.d.). Other than the high priority for privacy, Monero is very similar to Bitcoin.

Performance of Monero (XMR)							
Buy-and-hold returns		*Lowest Daily Returns*		*Highest Daily Returns*		*Average Daily Returns*	
2014	-72.83%	2014	-26.82%	2014	45.69%	2014	-0.10%
2015	1.00%	2015	-27.77%	2015	31.16%	2015	0.22%
2016	2667.81%	2016	-21.65%	2016	79.43%	2016	1.25%
2017	2398.43%	2017	-25.41%	2017	53.77%	2017	1.19%
2018	-63.85%	2018	-22.80%	2018	19.27%	2018	-0.30%
Full sample	8010.63%	Lowest (2015)	-27.77%	Highest (2016)	79.43%	Full sample	0.57%
Annualized Volatility		*Sharpe Ratio*		*Reference Sharpe Ratio (S&P500)*			
2014	190.69%	2014	-0.27	2014	0.99		
2015	120.09%	2015	0.66	2015	-0.03		
2016	165.79%	2016	2.70	2016	0.58		
2017	153.05%	2017	2.72	2017	2.15		
2018	133.94%	2018	-0.84	2018	0.19		
Full sample	153.53%	Full sample	1.35	Full sample	0.58		
Number of daily returns: 1502							

Table 5: Buy-and-hold returns, lowest daily returns, highest daily returns, average daily returns, annualized volatility, Sharpe Ratio, and a reference Sharpe Ratio for each different calendar year as well as for the full sample for Monero's daily price data.

Monero has the highest *buy-and-hold* returns over the full sample, compared to the other four cryptocurrencies. Furthermore, Monero's performance over 2016 trumps the performance of the other currencies over 2016. The high returns on Monero also come with very high annualized volatilities, however, the Sharpe Ratios of 2016 and 2017 remain very high.

4. Methodology

In order to see if the prices of bitcoin, Ripple, Litecoin, Dash, and Monero are efficient, two different approaches will be taken in this thesis. The methodology is therefore also divided into two parts. The first part involves multiple tests, both parametric and non-parametric, to see if the time-series of the cryptocurrency prices follow a random walk process. The second part of the methodology is about how new information is incorporated into the cryptocurrency prices, this will be tested using event study methodology.

4.1 Testing for a Random Walk

The Efficient Market Hypothesis (EMH) states that a (capital) market is efficient if its prices reflect all relevant information. This way it is impossible to 'beat the market', because the price an investor can trade at is the fair value of the asset he or she is trading. In the *weak-form* of the EMH, all past relevant information is incorporated into the prices. This past information is actually the information that previous price levels give when predicting future price levels. If the information in the past prices cannot be used to predict any future movements the weak-form of the EMH implies that prices in a market follow a *random walk*. If prices do in fact follow a random walk, their future levels are unpredictable, regardless of the method used to predict or estimate future values. The simplest form of a random walk model can be defined by the following first-order autoregressive process (AR(1)) (Brooks, 2014):

$$Y_t = \theta_1 Y_{t-1} + \varepsilon_t \tag{3}$$

where the error term (ε_t) is a stochastic variable, assumed to be independent and identically distributed with a mean of zero. As can be seen from equation (3), the value of a random walk process at a certain moment in time (Y_t) only depends on its own value in the previous time-period (Y_{t-1}) and an error term (ε_t). The coefficient of Y_{t-1} (θ_1) determines how strong the previous value influences the present value. In the case of a random walk process this coefficient is equal to one, the process is therefore a *unit root process*, meaning that it has a root process equal to one (unity). However, a random walk process does not have more than one root process equal to one. This means that the first difference of the random walk process does not contain a unit root, therefore the AR(1) model in equation (3) is integrated to the order of one (I(1).

The fact that a random walk process has a unit root means that all shocks from the past, which are all the previous values of the error term in equation (3), are permanent. The equation of the random walk process therefore implies that any value of Y_t is equal to Y_0 plus a sum of all random shocks up until that moment. This is the reason why a random walk process is impossible to predict. The current value of a random walk process is the best guess when trying to predict the value in the next time period, besides this there are no indicators as to where the process will move. Time-series can furthermore be a stationary or a non-stationary process, the difference between the two processes being their mean and variance. A stationary time-series process has a constant mean, as well as a constant variance, meaning both of them are independent of time. It is possible for a random walk process to have a constant mean, this is the case if the random walk does not have a drift, however, a random walk process will never have a time-independent variance. As stated before, all the stochastic changes in the value of a random walk are permanent, the variance of the random walk therefore increases over time. Because of the time dependence of the variance, the random walk process in equation (3) is, beside a unit root process, also a non-stationary process.

To test if the five different prices of the cryptocurrencies contain a unit root, and therefore follow a random walk, three different unit root tests will be performed. After testing for a unit root in the time-series of the prices, the unit root tests will also be performed on the first difference of the prices. If the cryptocurrency prices do in fact follow a random walk the prices itself will contain a unit root, whereas the first difference of the prices will not contain a unit root. The unit root tests which will be performed are the Augmented Dickey Fuller test, the Elliott-Rothenberg-Stock test, and the Phillips-Perron test. The reason to test for a unit root with three different tests is that unit root tests usually have a high *type I* *error*, which is the rejection of a true null-hypothesis. Therefore, three tests will be performed to see if they all yield the same conclusion. For each test the null-hypothesis is that the process follows a random walk, whereas the alternative hypothesis states that the process is stationary and does not follow a random walk. In addition to the unit root tests, the daily fluctuations of the cryptocurrency prices, the first difference of their time-series, will also be tested for randomness. If the prices follow a random walk, the daily price changes of the cryptocurrencies should be random values. To test if this is in fact the case, a runs test will be performed. The runs test is non-parametric test with the null-hypothesis that the daily price changes of the cryptocurrencies follow a random sequence and are therefore unpredictable.

4.1.1 Augmented Dickey Fuller Test

The Augmented Dickey Fuller Test (ADF) is an extension to the regular Dickey Fuller Test developed by Dickey and Fuller in 1979. The regular Dickey Fuller test uses Ordinary Least Squares (OLS) to fit the following model:

$$Y_t = \alpha + Y_{t-1} + \delta t + \varepsilon_t \tag{4}$$

This model is very similar to the simple model shown in equation (3), however, the model in equation (4) allows for the random walk to either have a drift (α), a time trend (δ_t), both, or neither. However, the coefficients of the regression in equation (4) will most likely be biased due to autocorrelation in Y_t, which in this case will be the daily value of any of the cryptocurrencies. The Augmented Dickey Fuller test therefore controls for autocorrelation by taking the first difference of Y_t as the dependent variable and adding lags of the first difference, this leads to the following equation:

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \delta t + \gamma 1 \Delta Y_{t-1} + \gamma \Delta Y_{t-2} + \cdots + \gamma k \Delta Y_{t-k} + \varepsilon_t \tag{5}$$

besides the addition of lags, equation (5) still has the allowance for a time trend and or a drift in the random walk process. The number of lags, a time trend, and a drift are all optional when using the ADF test, it is up to the user to include these or not. By default however, the ADF test tests for a random walk process without a drift. Regardless of the chosen options the ADF test then tries to identify if β in equation (5) is equal to one, which is the same as testing if θ_1, in equation (3), is equal to one. If β in equation (5) is found to be equal to one, the time-series contains a unit root, and is therefore non-stationary.

4.1.2 Elliott-Rothenberg-Stock Test

Elliot, Rothenberg, and Stock (1992) continue the work of Dickey and Fuller (1979) and create a similar unit root test, however, with a greater power then the ADF test. The modified version of the ADF test proposed by Elliott, Rothenberg, and Stock is also known as the DF-GLS test. The DF-GLS test tests the same hypotheses as the ADF test and uses the same equation to model the process, as shown in equation (4). The big difference between the DF-GLS test and the ADF test is that the DF-GLS test transforms the time-series via a generalized least square (GLS) regression, whereas the ADF test uses OLS. The DF-GLS test automatically includes both a constant and a trend term, therefore the DF-GLS test is proved to be the preferred option over the ADF test when the time-series has an unknown trend or mean. Another difference between the ADF test and the DF-GLS test is that the DF-GLS test automatically runs the test for every different lag number up until a maximum number of lags. The maximum number of lags is based on the Schwarz Information Criteria (SIC), defined as:

$$SIC = \ln\left(\widehat{rmse}^2\right) + (k+1)\,\frac{\ln(T - k_{max})}{(T - k_{max})} \tag{6}$$

where the Root Means Square Error (rmse) is calculated from the regression, and k is the number of lags. After running the test the DF-GLS outcome identifies the number of lags, between 1 and the previously defined maximum, which yields the lowest SIC. When running the ADF test, the number of lags need to be manually specified. Overall the DF-GLS test is found to be more powerful than the ADF test.

4.1.3 Phillips-Perron Test

Just like the DF-GLS test, the Phillips-Perron unit root test is a modification of the ADF test, the Phillips-Perron test therefore also uses equation (4) to model the process. The test, developed by Phillips and Perron (1988), tests similar hypotheses as the ADF test and the DF-GLS test, where under the null-hypothesis the process contains a unit root. The difference between the Phillips-Perron test and the ADF test, is that the ADF test uses lags of the first difference of Y_t to control for autocorrelation, while the Phillips-Perron test uses Newey-West (1986) standard errors to control for this. The number of lags used to calculate the standard error is set to $4*(T/100)^{2/9}$ by default, where T is the total number of observations. The number of Newey-West lags can however be adjusted by the user to the preferred setting.

4.1.4 Wald-Wolfowitz runs Test

Under the Random Walk Hypothesis (RWH) price changes, either positive or negative, should happen independently from the previous price change. This follows from the fact that the individual price changes should form a random sequence. In order to test whether or not this is the case, a Wald-Wolfowitz runs test will be performed. The test statistic of this test indicates if the first differences of the cryptocurrency prices, the absolute daily price changes, are independently and identically distributed. The test-statistic of the Wald-Wolfowitz runs test is expressed in the following way:

$$Z = \frac{R - \bar{R}}{\sigma_R} \tag{7}$$

$R =$ The number of runs in the sequence;

$\bar{R} =$ The expected number of runs in the sequence;

$\sigma_R =$ The standard deviation in the number of runs.

A run is defined as a series of daily price changes above or below the median price change of a cryptocurrency, once the run changes, for example from three price changes above the median to a price change below the median, the next run starts.

A price change above the median is defined as N_+ and a price change below the median is defined as N_-, with the total number of observations in the sequence being equal to $N_+ + N_-$. The expected number of runs, as well as the standard deviation in the number of runs can then be calculated as follows:

$$\bar{R} = \frac{2 * N_+ * N_-}{N} + 1 \tag{8}$$

$$\sigma_R = \sqrt{\frac{(\bar{R} - 1)(\bar{R} - 2)}{N - 1}} \tag{9}$$

The null-hypothesis of the Wald-Wolfowitz runs test is that the daily price changes form a random sequence, this null-hypothesis is rejected if the test statistic specified in equation (7) is, in absolute value, greater than the critical value.

4.2 Price Reactions Around News Events

The *weak-form* of the EMH implies that prices follow a random walk, as explained in the previous section of the methodology. The *semi-strong* form of the EMH hypothesizes that all relevant and publicly available information is incorporated into the prices. If prices reflect all publicly available information at any point in time, it means that new information needs to be incorporated into the price immediately. Furthermore, the incorporation of new information into the price needs to be appropriately, meaning that the price changes to the same degree as the importance of the information. The *semi-strong* form of the EMH therefore implies that price reactions following a news event do not display underreaction, implying that information is not immediately incorporated, or overreaction, implying the information is not incorporated appropriately. In order to see if the prices of the different cryptocurrencies react in line with the *semi-strong* form of the EMH to certain news events, 14 different news events will be used to perform an event study. The results of the event study methodology will be presented per coin, in order to highlight the possible differences in efficiency between the different cryptocurrencies. Furthermore, a distinction will be made between events with positive abnormal returns on the event date and events with negative abnormal returns on the event date. This way a potential difference between the price reaction after a positive event and the price reaction after a negative event can be documented.

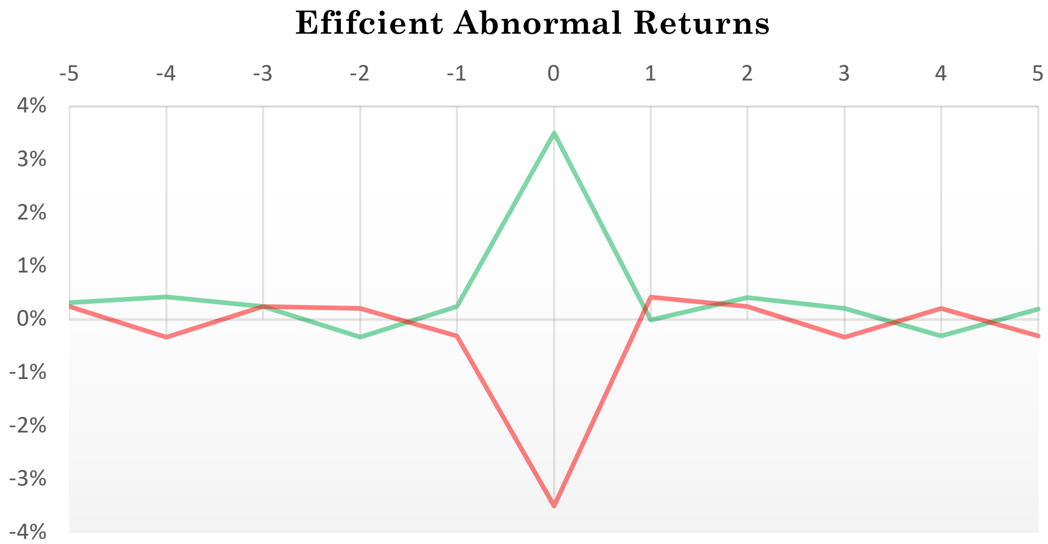
Among the 14 news events, the cryptocurrency directly related to that specific news event differs, two of the 14 events are expected to directly affect all five cryptocurrencies simultaneously. An overview of all news events and the respective cryptocurrencies directly related to each event can be found in the appendix (table A). The event studies will have an event period of 11 days, five days before the event date, the event date itself, and five days after the event date. This event period is relatively short, since most event studies use an event period of [-10,+10], however the high volatility in cryptocurrency prices will most likely lead to some significant price changes unrelated to the news event. Also, there a lot of different news events surrounding cryptocurrencies, possibly leading to interfering news events if the event period is too long. The limited event period is therefore a better option in order to isolate the effect of a news event. Beside the relatively short event period, the focus of the event studies will be on the day before the event date, the event date itself, and the day after the event, as it is expected that the biggest part of the reaction to the event happens in these three days.

When performing an event study on stock prices the returns on the event date are compared to the expected returns, this way the abnormal returns are being estimated. The abnormal returns are expressed in the following equation:

$$AR_{it}(Abnormal\ Return) = R_{it}(Realized\ Return) - E[R_{it}](Expected\ Return) \quad (10)$$

where the expected returns on a certain date are often based on a market model, like the CAPM, or a similar pricing model. However, the expected returns for the different cryptocurrencies cannot be estimated this way, because there are no generally accepted pricing models, yet, for cryptocurrencies. The realized returns on the different cryptocurrencies will therefore be compared to the returns over four different control periods: (1) the 15-day average returns on the cryptocurrency itself prior to the event period, (2) the 30-day average returns on the cryptocurrency itself prior to the event period, (3) the 15-day average returns on all five cryptocurrencies prior to the event period, and (4) the 30-day average returns on all five cryptocurrencies prior to the event period. This leads to four different calculations of the abnormal returns, the abnormal returns presented in the results are the average returns of the four previously described abnormal returns.

The graph on the next page, graph 1, shows the abnormal returns over an event period ranging from [-5, +5] during two fictitious events, a positive one and a negative one. The abnormal returns presented below indicate two efficient reactions, in line with the *semi-strong* form of the EMH. The news released during the two events is immediately incorporated into the price, indicated by abnormal returns close to zero on all days during the event period apart from the event date itself. A possible underreaction or overreaction would manifest itself in the days after the event. Taking the positive event as an example, if the abnormal returns after the event date remain positive, and not virtually equal to zero, this indicates that the initial abnormal return on the event date was too weak, or an underreaction. Likewise, negative abnormal returns on one or multiple days after the event date indicate an overreaction, which is then corrected on the days after the event.



Graph 1: Efficient abnormal returns during two fictitious events, with the event period on the x-axis and the abnormal returns on the y-axis. The green line indicates a positive event, whereas the red line indicates a negative event.

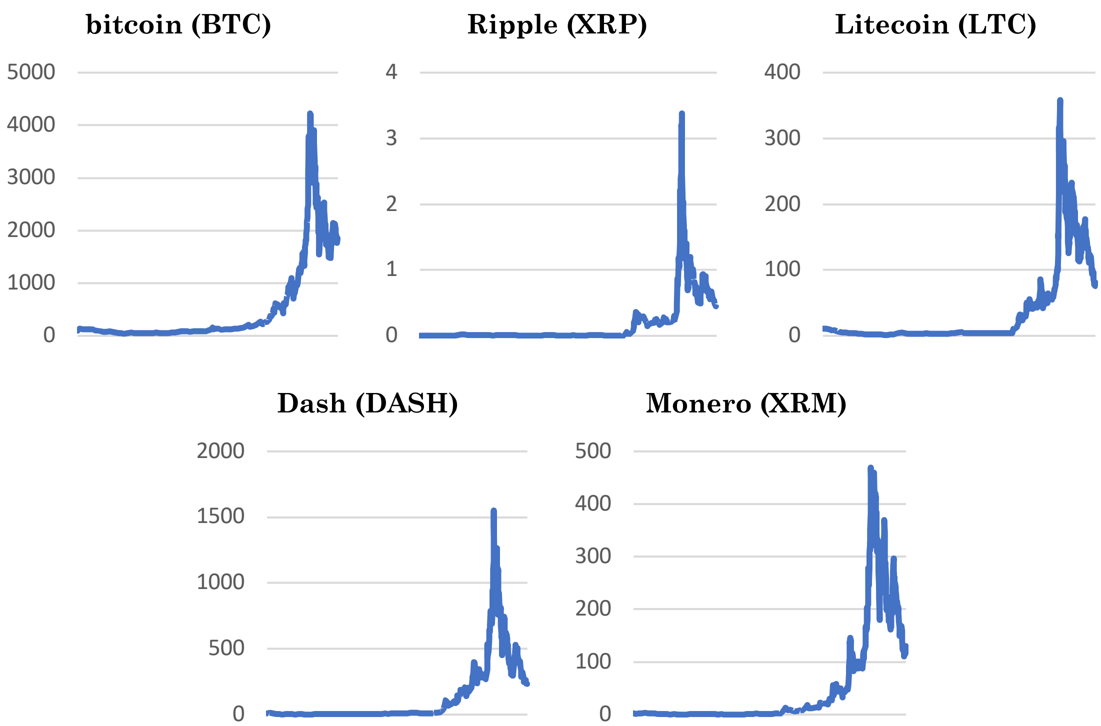
Other than the identification of underreaction or overreaction, the use of event studies can also help to see if events were anticipated. If the abnormal returns on day [-1] are of the same sign as the abnormal returns on the event date, this can be seen as prove of anticipation of the event in question.

5. Results

The results section follows the methodology in dividing the section into two parts. In the first part the results of the ADF, DF-GLS, Phillips-Perron, and sign tests are presented for all five cryptocurrencies and their first differences. The second part shows the results of 14 event studies to investigate how new information is incorporated into the prices of the cryptocurrencies.

5.1 Random Walk Hypothesis

The four tests in the first part of the results will showcase if the prices of the five cryptocurrencies follow a random walk, implying that they are impossible to predict. Graphs 2-6 show the price development of the five cryptocurrencies throughout the data sample. These graphs are used to judge whether or not the unit root tests should contain a trend term and or a constant term.



Graph 2-6: Price development ranging from 21 May 2014 – July 1 2018, for, from top left to bottom right: bitcoin, Ripple, Litecoin, Dash, and Monero. Values on the y-axis show the prices in US dollars.

For all five coins the graphs above show a clear upward trend, therefore in both the ADF test and the Phillips-Perron test a trend variable will be added to the regression, the DF-GLS test includes a trend term by default. Furthermore, the values do not have a zero-mean, the by default included constant term will therefore also be kept in the regressions of both tests. All time-series for the five cryptocurrency prices show a high order of autocorrelation, therefore a high number of lags should be included in the regression when performing the ADF and Phillips-Perron tests. To see if the results of the tests change alongside the number of lags, both tests will be performed using three different numbers of lags: 10, 15, and 20. The DF-GLS test points towards the optimal number of lags by default. The unit root tests on the daily price changes, the first difference of the prices, will not have a trend included, because these changes do not show a clear trend throughout time. The positive daily returns for all five cryptocurrencies, as showed in tables 1-5 in the data section, indicate that the default option of a constant term in the unit root tests for the first differences is the correct option. Furthermore, no lags will be added to the unit root tests on the first difference of the price data as all of the first differences show virtually no autocorrelation.

5.1.1 ADF test

Table 6 shows the test statistics for 15 ADF tests, three tests per cryptocurrency, with respectively 10, 15, and 20 lags added to the ADF regression. The critical values of the ADF test are reported in table 6 as well in, if the test statistic for any of the 15 ADF tests is, in absolute terms, bigger than the absolute value of -3.120 the null-hypothesis is rejected at the 10% significance level.

Augmented Dickey Fuller Test (Prices)

Significance Level	*Critical Value*	*Test Statisitc (Bitcoin)*		*Test Statisitc (Ripple)*	
10%	-3.120*	Lags (10)	-2.721	Lags (10)	-3.774**
5%	-3.410**	Lags (15)	-2.265	Lags (15)	-4.036***
1%	-3.960***	Lags (20)	-2.721	Lags (20)	-4.035***
Test Statistic (Litecoin)		*Test Statistic (Dash)*		*Test Statistic (Monero)*	
Lags (10)	-2.924	Lags (10)	-2.337	Lags (10)	-2.259
Lags (15)	-2.704	Lags (15)	-2.273	Lags (15)	-2.554
Lags (20)	-2.935	Lags (20)	-3.550**	Lags (20)	-2.998

Table 6: ADF test statistics for bitcoin, Ripple, Litecoin, Dash, and Monero, with three test statistics per cryptocurrency, showing the test outcome for 10, 15, and 20 lags. Critical values of the ADF test are reported in the top left, furthermore, * indicates 10% significance level, ** indicates 5% significance level, and *** indicates 1% significance level.

The test outcomes in table 6 show the same result for bitcoin, Litecoin, and Monero. For these three cryptocurrencies the null-hypothesis, which states that the time-series contains a unit root and therefore follows a random walk, is not rejected. The results for these currencies are in line with the *weak* form of the EMH. For Dash the null-hypothesis is rejected at the 5% significance level if the ADF regression includes 20 lags, this result indicates that the price of Dash does not follow a random walk. The results for Ripple are even stronger than those for Dash, at all number of lags displayed in table 6, the null-hypothesis is rejected. When 15 or 20 lags are added to the ADF regression, the test rejects the null-hypothesis even at the 1% significance level. Based on the results of the ADF tests above, so far the prices of Ripple and Dash do not seem to follow a random walk process.

Table 7 also shows the outcome of multiple ADF tests, one for each cryptocurrency this time. The test statistics reported in the table are the test statistics of the ADF tests on the first differences of the cryptocurrency prices.

Augmented Dickey Fuller Test (First Difference)			
Significance Level	*Critical Value*	*Test Statisitc (Bitcoin)*	*Test Statisitc (Ripple)*
10%	-3.120*	-35.790***	-35.912***
5%	-3.410**		
1%	-3.960***		
Test Statistic (Litecoin)		*Test Statistic (Dash)*	*Test Statistic (Monero)*
-36.236***		-43.248***	-44.080***

*Table 7: ADF test statistics for the first difference of bitcoin, Ripple, Litecoin, Dash, and Monero. Critical values of the ADF test are reported in the top left, furthermore, * indicates 10% significance level, ** indicates 5% significance level, and *** indicates 1% significance level.*

The reported values in table 7 yield the same result for each cryptocurrency as all test statistics reject the null-hypothesis of a random walk at the 1% significance level. This indicates that the first differences of the prices all follow a stationary time-series process, which corresponds with the characteristics of a random walk process. For bitcoin, Litecoin, and Monero the combined results of the ADF tests are therefore in line with the weak form of the EMH.

5.1.2 DF-GLS test

As stated in the methodology the DF-GLS test tests the same regression as the ADF test, the DF-GLS test does however regress the data using GLS. The DF-GLS tests are performed to see if the results are in line with the results of the ADF tests conducted above. Table 8 shows the *tau* test statistic of the DF-GLS test for all five cryptocurrencies, the test statistics shown are the ones with the number of lags yielding the lowest SIC score. The critical values of the DF-GLS test slightly differ when changing the number of lags and are therefore not included in the table, to indicate whether or not the test statistics are significant the same indicators as in table 6 and 7 have been added again.

DF-GLS Test (Prices)					
Test Statisitc (Bitcoin)		*Test Statisitc (Ripple)*		*Test Statistic (Litecoin)*	
Lags (20)	-2.310	Lags (18)	-3.913***	Lags (14)	-2.324
Test Statistic (Dash)		*Test Statistic (Monero)*			
Lags (21)	-3.483***	Lags (18)	-2.609*		

Table 8: DF-GLS tau test statistics for the number of lags yielding the lowest SIC for bitcoin, Ripple, Litecoin, Dash, and Monero, * indicates 10% significance level, ** indicates 5% significance level, and *** indicates 1% significance level.

Overall the results displayed in table 8 are in line with the outcomes of the ADF tests, making the ADF test outcomes more robust. The DF-GLS test rejects the null-hypothesis of a random walk at the 1% significance level for both Ripple and Dash. The results for bitcoin and Litecoin are still in line with the *weak* form of the EMH, whereas the DF-GLS test rejects the null-hypothesis for Monero, being it at only the 10% significance level. Even though the ADF test overwhelmingly rejects the null-hypothesis for all the first differences table 9 shows the DF-GLS test outcomes, for the sake of completeness, for the first differences as well. Again all test statistics are significant at the 1% significance level, indicating that the first differences of the cryptocurrency prices all follow a stationary process.

DF-GLS Test (Differences)		
Test Statisitc (Bitcoin)	*Test Statisitc (Ripple)*	*Test Statistic (Litecoin)*
-24.655***	-11.239***	37.050***
Test Statistic (Dash)	*Test Statistic (Monero)*	
-10.198***	-13.345***	

Table 9: DF-GLS test statistics for the first difference of bitcoin, Ripple, Litecoin, Dash, and Monero. The tests have been performed with zero lags added to the regression, furthermore, * indicates 10% significance level, ** indicates 5% significance level, and *** indicates 1% significance level.

So far the results for both bitcoin and Litecoin are still in line with the *weak* form of the EMH, whereas the results of the DF-GLS test show that Monero's price might be a stationary process. When adding at least 20 lags to the regression both the ADF test and the DF-GLS test indicate that the price of Dash does not follow a random walk. The results of the two tests also find the same result for Ripple, rejecting the null-hypothesis of a random walk regardless of the number of lags added to the regression.

5.1.3 Phillips-Perron test

The third, and last, unit root test performed on the price data of the five different cryptocurrencies and their first differences, is the Phillips-Perron test. The test automatically calculates two different test statistics, a *rho* test statistic, and a *tau* test statistic, for all tests performed both test statistics yield the same conclusion. Table 10 displays the outcome of 15 different Phillips-Perron unit root tests, to stay in line with the test statistics shown for the ADF and DF-GLS tests the displayed test statistics are the *tau* statistics. As was the case with the ADF test, the Phillips-Perron test is performed on each cryptocurrency using 10, 15, and 20 lags.

Phillips-Perron Test (Prices)					
Significance Level	*Critical Value*	*Test Statisitc (Bitcoin)*		*Test Statisitc (Ripple)*	
10%	-3.120*	Lags (10)	-2.245	Lags (10)	-3.932**
5%	-3.410**	Lags (15)	-2.310	Lags (15)	-3.890**
1%	-3.960***	Lags (20)	-2.315	Lags (20)	-3.897**
Test Statistic (Litecoin)		*Test Statistic (Dash)*		*Test Statistic (Monero)*	
Lags (10)	-2.898	Lags (10)	-2.328	Lags (10)	-2.350
Lags (15)	-2.884	Lags (15)	-2.334	Lags (15)	-2.400
Lags (20)	-2.858	Lags (20)	-2.455	Lags (20)	-2.494

Table 10: Phillips-Perron tau test statistics for bitcoin, Ripple, Litecoin, Dash, and Monero, with three test statistics per cryptocurrency, showing the test outcome for 10, 15, and 20 lags. Critical values of the Phillips-Perron test are reported in the top left, furthermore, * indicates 10% significance level, ** indicates 5% significance level, and *** indicates 1% significance level.

As can be seen from table 10 the Phillips-Perron test has the same critical values as the ADF test, furthermore the results of the two different unit root test are very similar. Again, the null-hypothesis is rejected for Ripple regardless of the number of lags. The difference with the ADF outcomes for Ripple, is that the Phillips-Perron test does not reject the null-hypothesis at the 1% significance level, only at the 5% significance level. Just as the ADF test the Phillips-Perron test does not reject the hypothesis of a random walk for bitcoin, Litecoin, or Monero. Another difference between the outcome of the ADF tests and the Phillips-Perron tests arises when looking at Dash, the ADF test with 20 lags added rejected the null-hypothesis for Dash at the 5% significance level, the Phillips-Perron test does not reject the null-hypothesis for Dash at all.

Table 11 shows the last unit root test results of this thesis, the outcomes shown in the table are those of the Phillips-Perron tests performed on the first differences of the cryptocurrency prices. Once again the reported test statistics are the *tau* test statistics of the Phillips-Perron test.

Phillips-Perron Test (First Difference)		
Test Statisitc (Bitcoin)	*Test Statisitc (Ripple)*	*Test Statistic (Litecoin)*
-35.690***	-36.369***	-36.347***
Test Statistic (Dash)	*Test Statistic (Monero)*	
-43.271***	-44.263***	

Table 11: Phillips-Perron tau test statistics for the first difference of bitcoin, Ripple, Litecoin, Dash, and Monero. The tests have been performed with zero lags added to the regression, furthermore, * indicates 10% significance level, ** indicates 5% significance level, and *** indicates 1% significance level.

Just like the ADF and the DF-GLS tests, the Phillips-Perron test also overwhelmingly rejects the null-hypothesis for the first differences of all five cryptocurrencies. The results for the first differences are therefore very clear as they all seem to follow a stationary process, meaning that the absolute price changes of the cryptocurrencies all have a time-invariant mean and variance.

5.1.4 Runs test

The unit root tests performed have shown that the absolute price changes of the cryptocurrencies all follow a stationary process, which is in line with a random walk process. However, besides being stationary, the successive price changes should also form a random sequence if they are generated by a random walk process. Table 12 displays the outcomes of a Wald-Wolfowitz runs tests for the first difference of bitcoin, Ripple, Litecoin, Dash, and Monero. The table reports the expected number of runs as well as the actual number of runs for each cryptocurrency, the *p*-value indicates whether or not the null-hypothesis of a random sequence is rejected.

Wald-Wolfowitz Runs Test					
Bitcoin		*Ripple*		*Litecoin*	
Expected Number of Runs	753	Expected Number of Runs	228	Expected Number of Runs	714
Number of Runs	768	Number of Runs	228	Number of Runs	784
P-value	0.289	P-value	0.000	P-value	0.000
Dash		*Monero*			
Expected Number of Runs	750	Expected Number of Runs	752		
Number of Runs	758	Number of Runs	764		
P-value	0.365	P-value	0.334		

Table 12: Wald-Wolfowitz runs test for randomness on the first difference of bitcoin, Ripple, Litecoin, Dash, and Monero.

The p-values in table 12 show that the null-hypothesis is not rejected for bitcoin, Dash, or Monero. This means that the absolute daily price changes of these three cryptocurrencies follow a random sequence, which is in line with the *weak* form of the EMH. The null-hypothesis of randomness is however rejected for both Ripple and Litecoin, indicating that the price changes of Ripple and Litecoin are not random.

5.1.5 Weak Form Market Efficiency

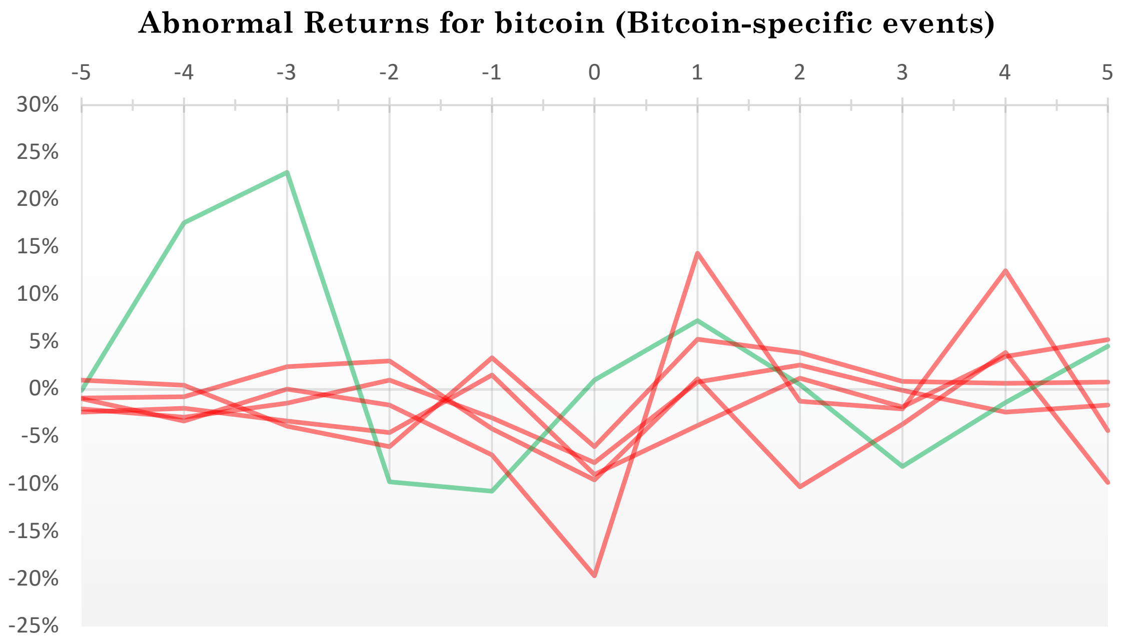
Three parametric and one non-parametric test have been performed on the price data of bitcoin, Ripple, Litecoin, Dash, and Monero. All tests yield the same conclusion for bitcoin, indicating that the price of bitcoin follows a unit root process and that the the absolute daily price changes of bitcoin are random. Based on these results the price of bitcoin is considered to be efficient according to the *weak* form of the EMH. The price of Ripple is found to be inefficient as all tests reject the hypothesis that it follows a unit root process, or a random walk. For Dash and Monero the results are mixed. The ADF and DF-GLS test indicate that the price of Dash does not follow a random walk, the Phillips-Perron test does however not reject the null-hypothesis of a random walk. For Monero the null-hypothesis is only rejected by the DF-GLS test, and only at the 10% significance level, however based on this rejection Monero's priced is not considered to be efficient. Litecoin's price looks efficient based on all parametric tests, its absolute price changes are however not random, based on the Wald-Wolfowitz runs test. Based on these results only bitcoin's price is considered to be *weak* form efficient.

5.2 Price Reactions – Event Study Methodology

The high volatility in cryptocurrency prices is partly driven by the high quantity of news events surrounding the currencies. To see if the prices react appropriately, in line with the *semi-strong* form of the EMH, to news events, 14 event studies are performed. The results are presented with two graphs per cryptocurrency. The difference between the two graphs presented is that one of them shows the abnormal returns around events directly related to that cryptocurrency, and the other one shows the abnormal returns around events directly related to a different cryptocurrency. Furthermore, the positive and negative events in each graph are separated by the use of color.

5.2.1 Price Reactions: BTC

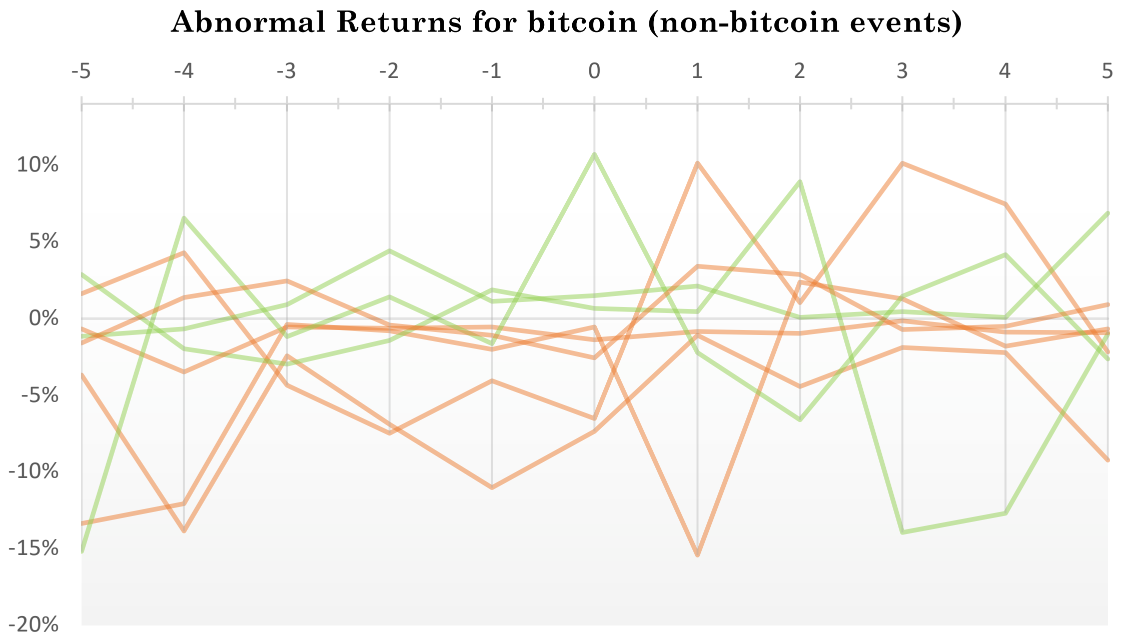
Graph 7 display the abnormal returns for bitcoin around six news events directly aimed at bitcoin. Five of the six events are negative, whereas the sixth is a positive event. The graph shows the daily abnormal returns over the event period [-5, +5], where day 0 is the event date.



Graph 7: Abnormal returns for bitcoin over the event period [-5, +5] around six events directly related to Bitcoin, with the event period on the x-axis and the abnormal returns on the y-axis. A green line indicates a positive event, whereas a red line indicates a negative event.

Four of the five negative abnormal returns on the event dates show signs of overreaction, as the negative abnormal returns for these four events turn positive on day [+1]. The positive abnormal returns on the day after the event date correct the initial overreaction. Furthermore, three out of the five negative events seem to have been anticipated, as the abnormal returns on day [-1] for these events are also negative. The positive event in graph 7 does not display overreaction, the abnormal returns on the two days following the event remain positive, this could however be a sign of underreaction, where the positive abnormal returns on the event date are too weak. The over- and underreaction displayed in graph 7 are violations of the *semi-strong* form of the EMH.

Graph 8 shows eight events not directly related to bitcoin. Out of these eight events, three of them yield positive abnormal returns on the event date, and five yield negative abnormal returns on the event date.

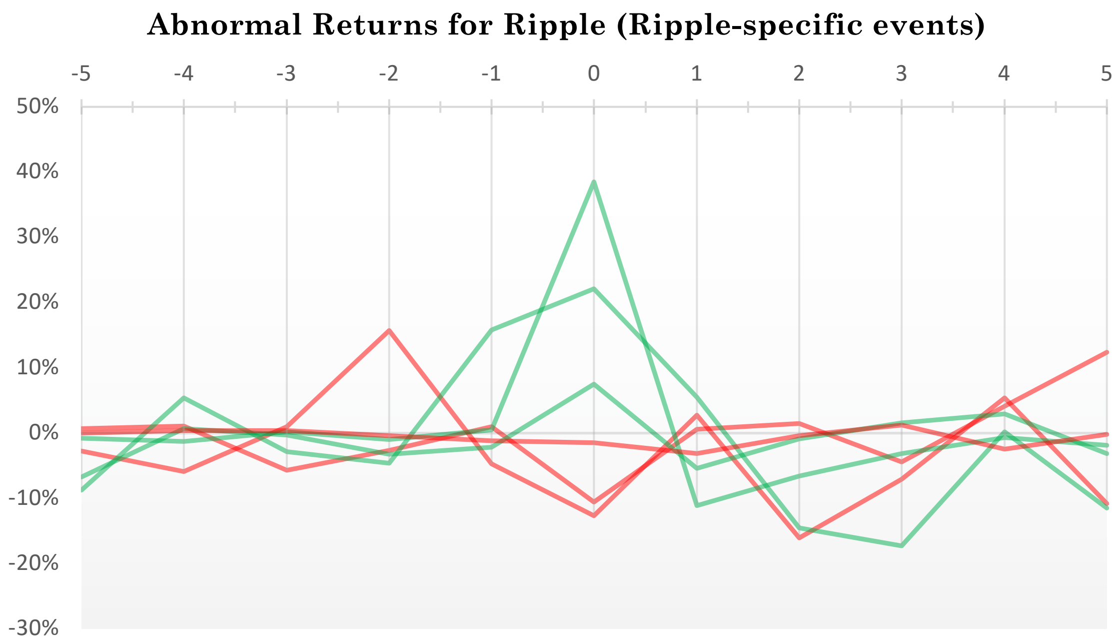


Graph 8: Abnormal returns for bitcoin over the event period [-5, +5] around six events not directly related to Bitcoin, with the event period on the x-axis and the abnormal returns on the y-axis. A mint green line indicates a positive event, whereas an orange line indicates a negative event.

First of all bitcoin reacts quite heavily on news events not directly related to itself, as can be seen in graph 8, which shows that the abnormal returns do not equal zero around the event date for any of the events. Furthermore, the abnormal returns show the same over- and underreactions as documented in graph 7. Out of the three positive events, two of them show underreaction, indicated by the positive abnormal return on the two days after the event date. The other positive event shows clear overreaction, indicated by the negative abnormal returns on the day after the event date. Looking at the negative events, two of them show a high overreaction on the event date. These two events are followed by high positive abnormal returns on the day after the event, approximately 4% and 10%. One of the negative events also shows a high underreaction, with a negative abnormal return of -15% on day [-1]. The abnormal returns for bitcoin, around events not directly related to this specific cryptocurrency, also violate the *semi-strong* form of the EMH.

5.2.2 Price Reactions: XRP

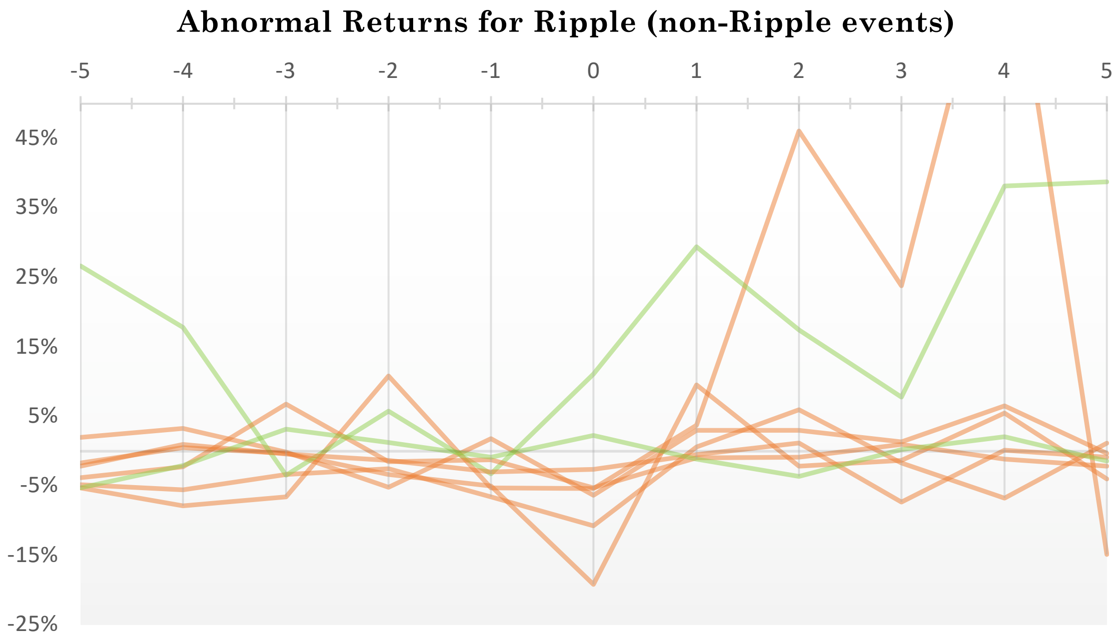
Graph 9 displays six events all of which are directly related to Ripple, three of the six events can be identified as positive, whereas the other three yield negative abnormal returns on the event dates. The graph shows the daily abnormal returns over the six event periods [-5, +5], where day 0 is the event date.



Graph 9: Abnormal returns for Ripple over the event period [-5, +5] around six events directly related to Ripple, with the event period on the x-axis and the abnormal returns on the y-axis. A green line indicates a positive event, whereas a red line indicates a negative event.

The event yielding the highest positive abnormal return on the event date in graph 9 is followed by a correction in the form of a negative abnormal return of minus 10%. The initial positive reaction is therefore classified as an overreaction. The price reactions to the other two positive events are not efficient either, one of them is also corrected on the day after the event by a negative abnormal return of -5%, and the other one is followed by another positive abnormal return. The positive events in graph 9 therefore show both underreaction and overreaction. Out of the three negative events, two of them show overreaction and one of them shows underreaction. It is also worth noting that the overreaction during the negative events is much smaller than the overreaction during the positive events.

Graph 10 shows the abnormal returns for Ripple around the eight events not directly related to the cryptocurrency. Just as graph 9, the graph shows the daily abnormal returns over the eight event periods [-5, +5], where day 0 is the event date. One observation in graph 10 is not displayed, this observation is an abnormal return of +81% on day [+4], the choice not to display this observation is made to make the abnormal returns around the other events more visible.

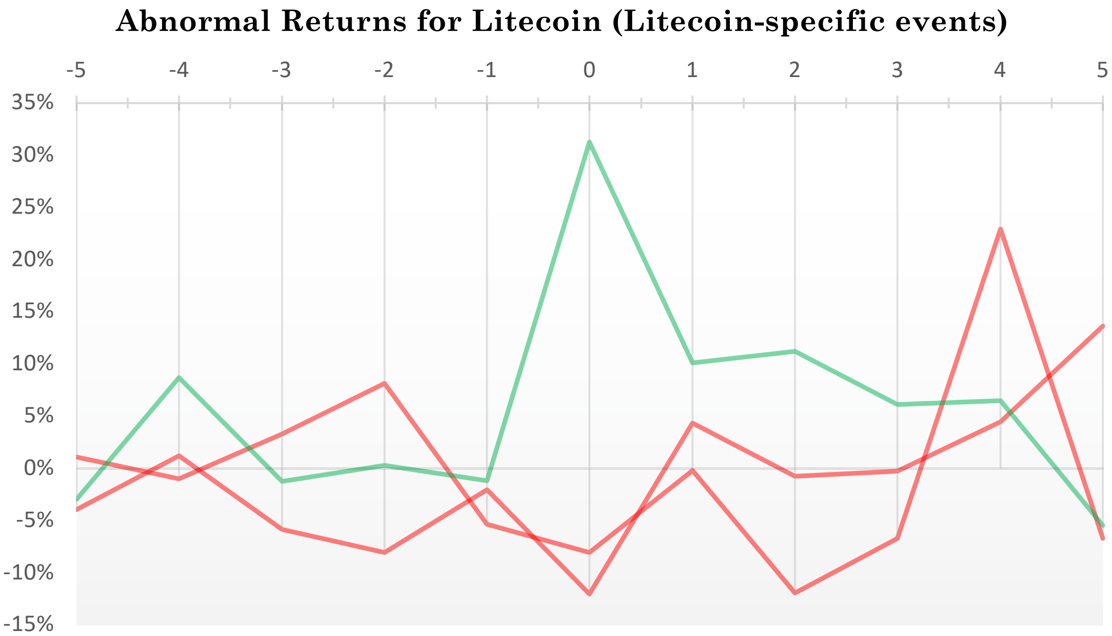


Graph 10: Abnormal returns for Ripple over the event period [-5, +5] around eight events not directly related to Ripple, with the event period on the x-axis and the abnormal returns on the y-axis. A mint green line indicates a positive event, whereas an orange line indicates a negative event.

All negative events displayed in graph 10 have negative abnormal returns on the day prior to the event date, indicating that the events were most likely expected. Just like bitcoin, Ripple reacts strongly to events not directly related to itself, with a positive abnormal return of 11% on an event date as prime example. The event yielding this abnormal return shows an even higher abnormal return the day after the event (+29%), this implies that the initial reaction can be classified as an underreaction, which is furthermore confirmed by the fact that the abnormal returns stay positive throughout the whole event period. The extremely high abnormal return on day [+4] during one of the event periods, the observation not displayed in graph 10, seems to be unrelated with the actual event as the negative abnormal return on the event date of that event is not nearly as strong as the positive return following it. Four out of the other five negative events in graph 10 show overreaction as the negative abnormal returns on the event dates are followed by positive abnormal returns on the next day.

5.2.3 Price Reactions: LTC

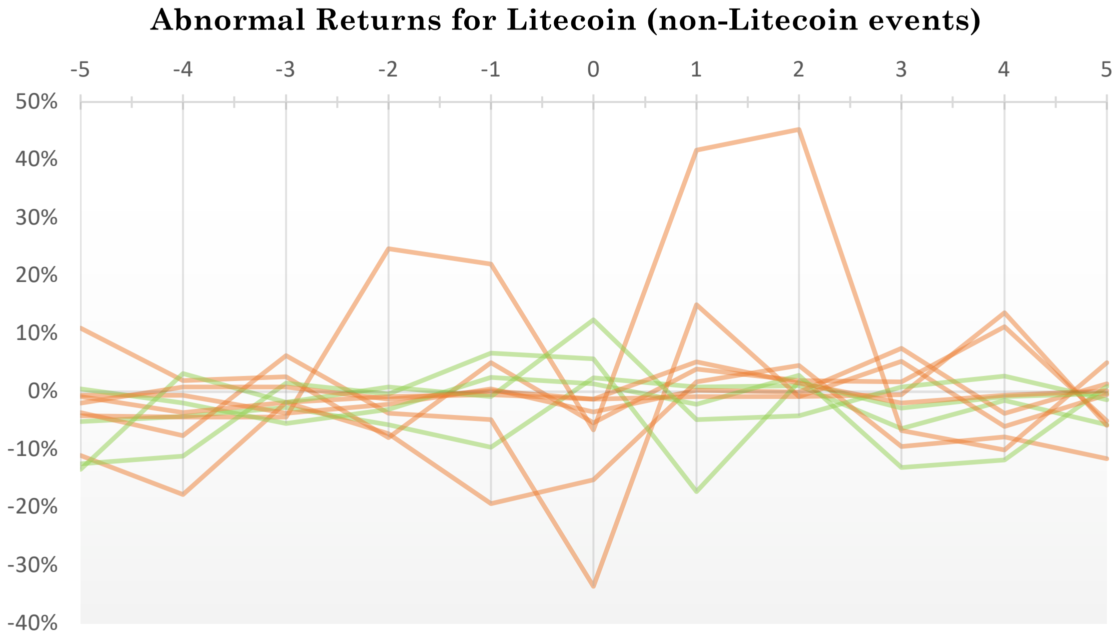
Graph 11 displays the abnormal returns of Litecoin throughout the event period, [-5, +5], of three events directly related to Litecoin. Two out of the three events can be identified as negative events, and one of them as a positive event.



Graph 11: Abnormal returns for Litecoin over the event period [-5, +5] around three events directly related to Litecoin, with the event period on the x-axis and the abnormal returns on the y-axis. A green line indicates a positive event, whereas a red line indicates a negative event.

One of the two negative events shown in graph 11 displays a small overreaction, since the negative abnormal return on the event date is corrected by a positive abnormal return the day after the event date. The positive event in graph 11 displays underreaction as the abnormal returns stays positive for four consecutive days following the event date. The two negative events were most likely anticipated as the abnormal returns prior to those events are also negative, the positive event does not show any sign of anticipation.

Graph 12 shows the abnormal returns throughout the event period for the 11 events not directly related to Litecoin. Four of the 11 events yield a positive abnormal return for Litecoin on the event date. None of the abnormal returns on the event dates are equal to zero, indicating that Litecoin strongly reacts to news even though this news is not directly related to Litecoin.

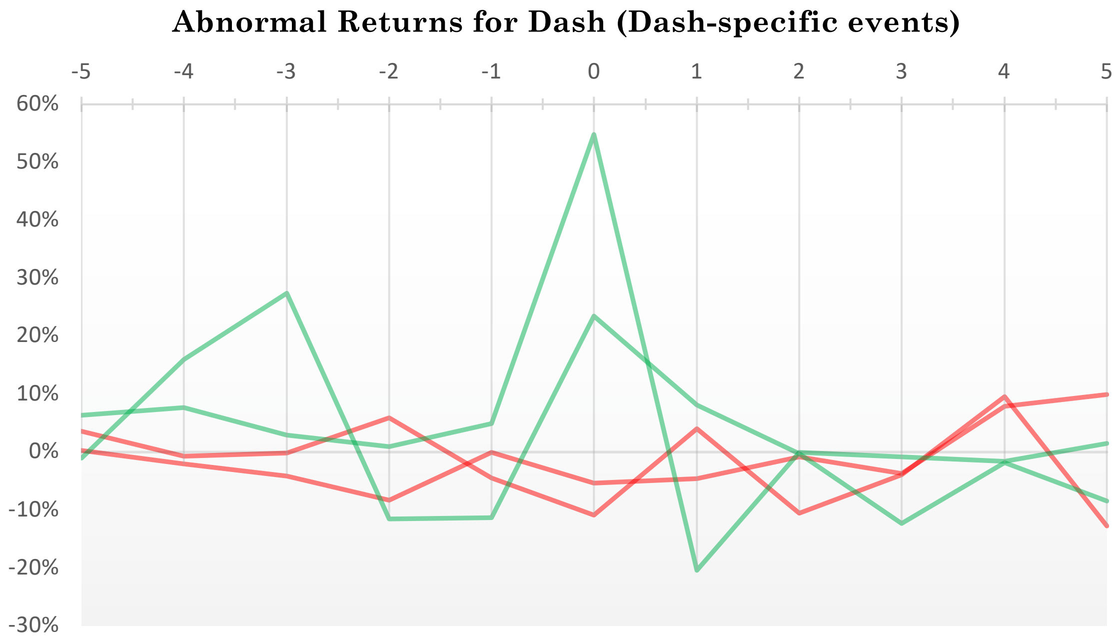


Graph 12: Abnormal returns for Litecoin over the event period [-5, +5] around 11 events not directly related to Litecoin, with the event period on the x-axis and the abnormal returns on the y-axis. A mint green line indicates a positive event, whereas an orange line indicates a negative event.

Three of the four positive events displayed in graph 12 show an overreaction, as their positive abnormal returns on the event date are corrected during the first day following the event by negative abnormal returns. When looking at the seven negative events only one of them does not show overreaction. The one negative event with very high positive abnormal returns on the day before and after the event date seems to be unrelated to the actual event as this behavior makes no sense.

5.2.4 Price Reactions: DASH

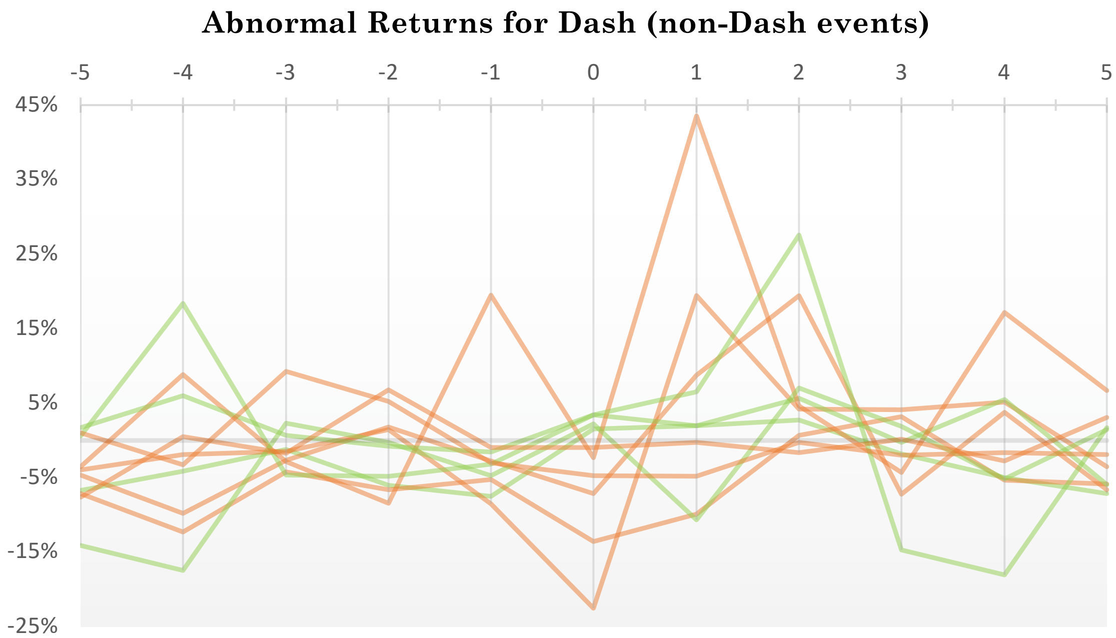
Graph 13, on the next page, shows the abnormal returns for Dash around four events directly related to Dash itself. Half of the events yield positive abnormal returns, whereas the other half yields negative abnormal returns on their respective event dates.



Graph 13: Abnormal returns for Dash over the event period [-5, +5] around four events directly related to Dash, with the event period on the x-axis and the abnormal returns on the y-axis. A green line indicates a positive event, whereas a red line indicates a negative event.

The two positive abnormal returns on the event dates in graph 13 are quite high, this might be due to the fact that both events involve an event which makes Dash more widely available to possible users of the cryptocurrency. The event date with the highest positive abnormal return is however followed by a negative abnormal return of -20%, which makes the initial abnormal return an overreaction. The other positive event is followed by two positive abnormal returns on the days after the event, which indicates that the initial price reaction can be called an underreaction. The same goes for the two negative events, one of them shows an overreaction, while the other one shows an underreaction. When comparing the overreaction and underreaction during the positive events with the negative events, both reactions are stronger for the positive events.

Just as the previous three cryptocurrencies, bitcoin, Litecoin, and Ripple, Dash strongly reacts to news events which are not directly related to the cryptocurrency itself. This can be seen in graph 14 which shows the abnormal returns for Dash around the 10 events related to other cryptocurrencies.

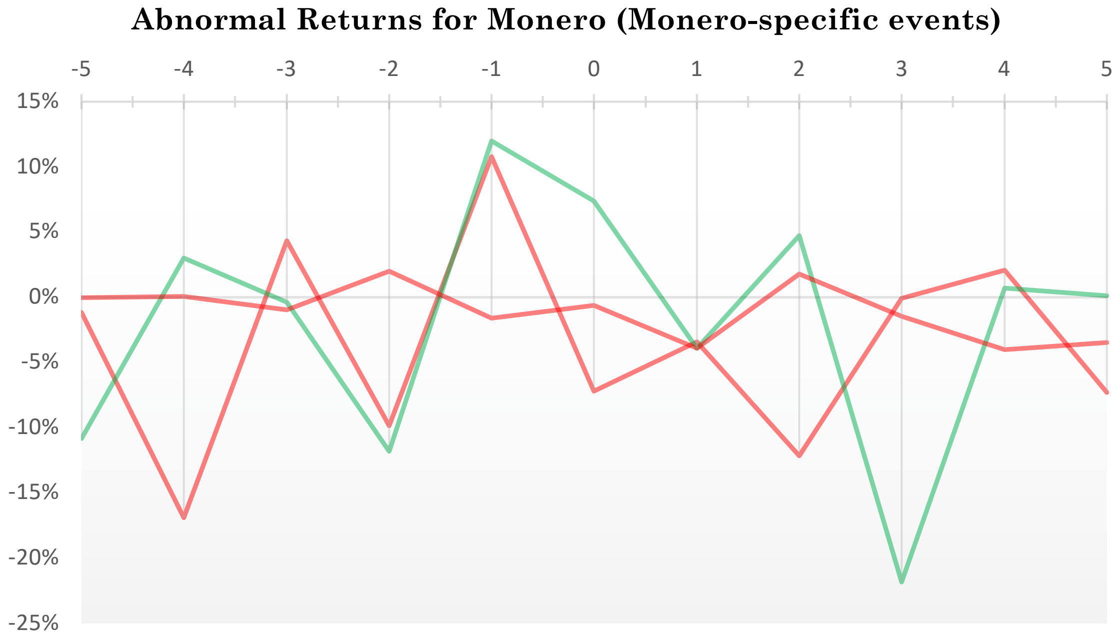


Graph 14: Abnormal returns for Dash over the event period [-5, +5] around 10 events not directly related to Dash, with the event period on the x-axis and the abnormal returns on the y-axis. A mint green line indicates a positive event, whereas an orange line indicates a negative event.

The event in graph 14 yielding an abnormal return on day [+1] of +44% seems to be an inefficient and random price reaction as the negative abnormal return on the event date is only -2%. This high positive abnormal return does therefore not seem to be a correction for the initial negative abnormal return. Three out of the other five negative events in graph 14 show overreaction, indicated by positive abnormal returns on the day after the event date. One of the four positive events also shows overreaction, whereas the other three show underreaction. The overreaction during the negative events seems to be bigger in absolute value than the overreaction during the positive events.

5.2.5 Price Reactions: XRM

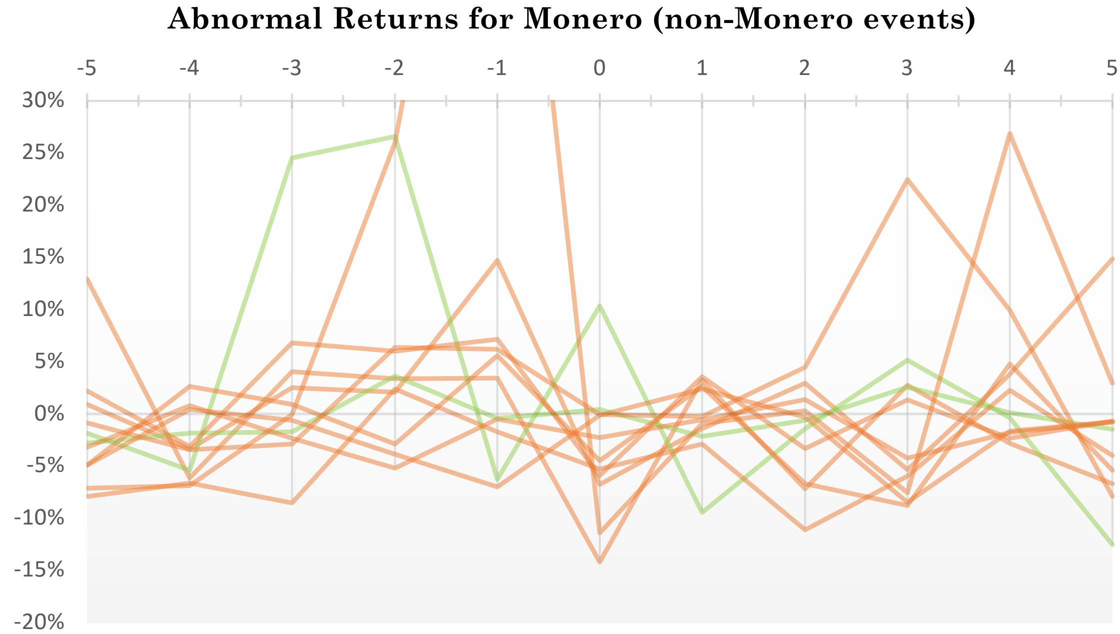
The fifth and last cryptocurrency to be tested on efficiency, to the degree of the *semi-strong* form of the EMH, is Monero. Graph 15, displayed on the next page, shows Monero's abnormal returns over the event period around three Monero-specific news events.



Graph 15: Abnormal returns for Monero over the event period [-5, +5] around three events directly related to Monero, with the event period on the x-axis and the abnormal returns on the y-axis. A green line indicates a positive event, whereas a red line indicates a negative event.

The positive Monero-specific news event displayed in graph 15 shows an overreaction, this is indicated by the negative abnormal return of -4% on day [+1] after the positive abnormal return of +7% on the event date. Both negative events displayed in graph 15 show underreaction. The results for the Monero-specific events are similar to the results of Ripple and Dash for their respective coin-specific events. For these three cryptocurrencies there seems to be more and stronger overreaction during the positive events than during the negative events.

The last graph of the results section, graph 16, displayed on the next page, shows the abnormal returns for Monero over the remaining 11 news events not directly related to Monero. Just like all other cryptocurrencies the abnormal returns in graph 16 are all different from zero on the event dates, which shows that Monero also strongly reacts on news related to other cryptocurrencies. Only two of the 11 news events displayed in the graph have positive abnormal returns on the event dates, the other nine events all display negative abnormal returns on day [0]. Both positive events display overreaction, one of which is relatively small, while the other one is quite substantial. The negative events display overreaction in four of them, and underreaction in the other five, again the overreaction during positive events is bigger in value than the overreaction, or even underreaction, during negative events.



Graph 16: Abnormal returns for Monero over the event period [-5, +5] around 11 events not directly related to Monero, with the event period on the x-axis and the abnormal returns on the y-axis. A mint green line indicates a positive event, whereas an orange line indicates a negative event.

5.2.6 Semi-Strong Form Market Efficiency

The results of the 14 event studies show that none of the tested cryptocurrencies follow the *semi-strong* form of the EMH. All of the cryptocurrencies display both overreaction and underreaction which are clear violations of the EMH in its *semi-strong* form. Furthermore, all cryptocurrencies react heavily on news events not directly related to them, even though this is not per definition inefficient behavior it is striking that literally all cryptocurrencies react heavily to all news events tested in this thesis. For bitcoin and Litecoin there is no clear pattern when looking at positive and negative events, both of them seem to showcase both overreaction and underreaction at an approximately equal quantity. When looking at the events directly related to themselves, Ripple, Dash, and Monero do display overreaction more frequently during positive events than during negative events. The overreaction documented in the positive events is also bigger in absolute value.

6. Conclusion

The conclusion section concludes this thesis by looking at three aspects: (1) the answers to the hypotheses and the research question, (2) the implications and relevance of this thesis, and (3) the limitations of this thesis and recommendations regarding future research. This section helps to get a clear overview of the results described in the results section and answers the research question.

6.1 Hypothesis Testing and Answering the Research Question

Based on the results of the three unit root tests and the Wald-Wolfowitz runs test the first and second hypothesis can be answered. The first hypothesis stated that the cryptocurrency prices follow a stationary process, while the second hypothesis stated that the absolute price changes do not happen at random. The results of this thesis show that both hypotheses are wrong for bitcoin's price. The price of bitcoin actually follows a random walk, implying that the process is non-stationary, and its absolute price changes form a random sequence, meaning that the price of bitcoin is efficient in the *weak* form of the EMH. For Ripple, Dash, and Monero, the first hypothesis turns out to be true, as they do not follow random walks. Litecoin's price did seem to follow a random walk according to the unit root tests performed, the Wald-Wolfowitz runs test showed, however, that the absolute price changes of Litecoin do not form a random sequence. Therefore, the first hypothesis is found to be wrong for Litecoin, whereas the second one is found to be true. Besides Litecoin, Ripple is the only cryptocurrency in this thesis for which the second hypothesis is also found to be true. The absolute price changes of the other three cryptocurrencies actually form random sequences.

The third, fourth, and fifth hypothesis are answered using the event study methodology. The third hypothesis, stating that the cryptocurrency prices are not efficient in the *semi-strong* form of the EMH, is found to be true for all five cryptocurrencies used in this thesis. The event study methodology identifies both overreaction and underreaction for all five cryptocurrencies, which violates the EMH in its *semi-strong* form. The fourth hypothesis expected overreactions to happen more frequently when looking at negative events, than when looking at positive events. The opposite is actually found for Ripple, Dash, and Monero. For both bitcoin and Litecoin overreaction does not seem to be more frequent in any of the event types. Therefore, the fourth hypothesis is found to be false for all five cryptocurrencies. The fifth and last hypothesis is rejected by the event study results for bitcoin, Litecoin, Ripple, Dash, and Monero. Both the fourth and fifth hypothesis are therefore found to be false for all five cryptocurrencies in this thesis.

The research question of this thesis reads: *"Do cryptocurrency prices move in line with the Efficient Market Hypothesis?"*, the short answer would be: no they do not. However, there is a distinction to be made between three forms of efficiency, and the five cryptocurrencies used in this thesis may not represent all other cryptocurrencies out there. The results of this thesis actually show that the price of bitcoin is efficient in the *weak* form of the EMH, however, when investigating the *semi-strong* form, the price of bitcoin is found to be inefficient. Of the other four cryptocurrencies, none are found to be efficient in any of the three forms. The answer to the research question can therefore also be stated as: partly. The cryptocurrency currently available for the longest period of time, bitcoin, shows a sign of efficiency, this may indicate that cryptocurrencies may become more efficient when getting older, or more mature. However, whether this is true is currently only speculation and should be investigated in the future.

6.2 Implications and Relevance

As stated in the introduction, the implications and relevance of this thesis applies to three groups of people. When considering the results of the thesis now, risk managers are not very likely to use cryptocurrencies to diversify risk at this moment in time, as cryptocurrency prices exhibit multiple behavioral biases in the form of both overreaction and underreaction. For regulators, there seems to be plenty of room to regulate the exchange in cryptocurrencies, as the prices do not appear to react in efficient ways. If this regulation is needed is however a question that remains unanswered based on the results of this thesis. Lastly, for investors, the results imply that technical analysis cannot be used to predict the price of bitcoin, because its price follows a random walk process. For the other four cryptocurrencies, technical analysis may have some power to predict prices, if the right model is found to predict these prices. Furthermore, the prices of cryptocurrencies showcase overreaction and underreaction during news events for all five cryptocurrencies used in this thesis. This makes it hard for both current and possible future investors to judge whether or not certain moments are a good time to buy or sell a certain cryptocurrency.

The rejection of the fourth hypothesis of this thesis is in contrast with the results of Catani and Grassi (2017), who find an asymmetric reaction in the volatility of cryptocurrency prices after either a positive or a negative price change. The loss aversion among cryptocurrency investors identified by the authors is not found in this thesis. Furthermore, previous literature has identified certain price drivers for cryptocurrencies, and concluded that the currencies may not be actual currencies (Yermack, 2015). However, previous literature has not identified whether the prices of cryptocurrencies are efficient, so in this regard, the results of this thesis add knowledge about cryptocurrencies to the current literature.

6.3 Limitations and Recommendations for Future Research

This thesis only uses five cryptocurrencies to assess cryptocurrencies in general, the decision to only use five of them is based on the available data, as more data becomes available in the future more cryptocurrencies can be added to research similar to this thesis. However, based on the result found in this thesis it is not expected that any other cryptocurrencies are *weak* form efficient, or even more than that. Furthermore, the abnormal returns used in this research are calculated based on average returns preceding the event periods, it might be possible to calculate abnormal returns based on a pricing model in the future, which might then possibly alter the outcomes of the event studies.

Overall, the most interesting aspect of cryptocurrencies to research might be the actual risk involved in them, similar to how systematic and idiosyncratic risk for stocks has been identified. More specifically related to the results found in this thesis, and following from a limitation of it, it might be interesting to see if the results do in fact not change when adding more cryptocurrencies. Also, as already briefly mentioned, it might be possible that cryptocurrencies gain efficiency over time, by dividing similar data as the data used in this thesis into multiple time samples it could be investigated if the efficiency has improved over time. Furthermore, the behavior of cryptocurrency traders can be investigated further besides the identification of under- and overreaction in this thesis. For example, using survey data, the motives and types of investors can possibly be identified giving more insight into trading behavior. Lastly, the US Justice Department has recently launched an investigation regarding the price manipulation of certain cryptocurrency prices (Robinson, 2018), maybe a research similar to this thesis can identify unexpected and ungrounded price changes, pointing towards possible price manipulations.

7. References

Badev, A., Chen, M., 2014. Bitcoin: Technical background and data analysis. *FEDS Working Paper*, No. 104.

Barber, S., Boyen, X., Shi, E., Uzun, E., 2012. Bitter to better: how to make bitcoin a better currency. *International Conference on Financial Cryptography and Data Security*, 399-414.

Barberis, N., Thaler, R., 2003. A survey of behavioral finance. *Handbook of the Economics of Finance* 1, 1053-1128.

Bondt, de, W.F., Thaler, R., 1985. Does the stock market overreact?. *The Journal of finance* 40, 793-805.

Brodsky, W.J., 1994. The Globalization of Stock Index Futures: A Summary of the Market and Regulatory Developments in Stock Index Futures and the Regulatory Hurdles Which Exist for Foreign Stock Index Futures in the United States. *Northwestern Journal of International Law & Business* 15, 248-302.

Brooks, C. 2014. Introductory econometrics for finance. Cambridge University Press, Cambridge.

Catania, L., Grassi, S., 2017. Modelling Crypto-Currencies Financial Time-Series. *CEIS Working Paper*, No 417.

Cboe Exchange Inc., 2018. XBT Bitcoin Futures. *Retrieved from:* http://cfe.cboe.com/products/bitcoin-qrg.pdf.

CoinMarketCap, n.d. Number of Cryptocurrencies. *Retrieved from:* https://coinmarketcap.com.

Dash, n.d. Project Information, Dash Documentation. *Retrieved from:* https://www.dash.org.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association* 74, 427-431.

Elliott, G., Rothenberg, T.J., Stock, J.H., 1992. Efficient tests for an autoregressive unit root. *Econometrica*, 813-836.

Fama, E.F., 1963. Mandelbrot and the stable Paretian hypothesis. *The journal of business* 36, 420-429.

Fama, E.F., 1965a. The behavior of stock-market prices. *The journal of Business* 38, 34-105.

Fama, E.F., 1965b. Random walks in stock market prices. *Financial analysts journal* 51, 75-80.

Fama, E.F., Malkiel, B.G., 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance* 25, 383-417.

FindLaw, n.d. What is the Howey Test? *Retrieved from:* [*https://www.consumer.findlaw.com/securities-law/what-is-the-howey-test.html*](https://www.consumer.findlaw.com/securities-law/what-is-the-howey-test.html).

Grinberg, R., 2012. Bitcoin: An innovative alternative digital currency. *Hastings Science & Technology Law Journal* 4, 159-181.

Hayes, A.S., 2017. Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics* 34, 1308-1321.

Kristoufek, L., 2013. BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific reports* 3, 3415.

Kroll, J.A., Davey, I.C., Felten, E.W., 2013. The economics of Bitcoin mining, or Bitcoin in the presence of adversaries. *Proceedings of WEIS,* Vol. 2013, p. 11.

Litecoin, n.d. What is Litecoin?. *Retrieved from:* [*https://www.litecoin.org*](https://www.litecoin.org).

Marsh, A., 2018. Traders With Pockets Full of Crypto Quit Wall Street. *Retrieved from:* [*https://www.bloomberg.com/news/articles/2018-05-30/traders-with-pockets-full-of-cryptocurrencies-quit-wall-street?srnd=cryptocurriences*](https://www.bloomberg.com/news/articles/2018-05-30/traders-with-pockets-full-of-cryptocurrencies-quit-wall-street?srnd=cryptocurriences).

Malkiel, B.G., 1989. Efficient Market Hypothesis. *Finance*, 127-134.

Monero, n.d. User guides, Wallets. *Retrieved from:* [*https://www.getmonero.org*](https://www.getmonero.org).

Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system. *Retrieved from:* [*https://bitcoin.org/bitcoin.pdf*](https://bitcoin.org/bitcoin.pdf).

Pisani, B., 2018. Bitcoin and ether are not securities but some initial coin offerings may be, SEC official says. *Retrieved from:* [*https://www.cnbc.com/2018/06/14/bitcoin-and-ethereum-are-not-securities-but-some-cryptocurrencies-may-be-sec-official-says.html*](https://www.cnbc.com/2018/06/14/bitcoin-and-ethereum-are-not-securities-but-some-cryptocurrencies-may-be-sec-official-says.html).

Ripple, n.d. Global Payments, Ripple Overview. *Retrieved from:* [*https://www.ripple.com*](https://www.ripple.com).

Robinson, M., 2018. SEC tries to scam ICO investors to show them how easy it is. *Retrieved from: https://www.bloomberg.com/news/articles/2018-05-16/sec-tries-to-scam-ico-investors-to-show-them-how-easy-it-is.*

Robinson, M., Schoenberg, T., 2018. Bitcoin manipulation is said to be focus of US criminal probe. *Retrieved from:* [*https://www.bloomberg.com/news/articles/2018-05-24/bitcoin-manipulation-is-said-to-be-focus-of-u-s-criminal-probe*](https://www.bloomberg.com/news/articles/2018-05-24/bitcoin-manipulation-is-said-to-be-focus-of-u-s-criminal-probe).

Samuelson, P.A., 1965. Proof that properly anticipated prices fluctuate randomly. *Industrial management review* 6, 41-49.

Sharpe, W.F., 1994. The Sharpe ratio. *Journal of portfolio management* 21, 49-58.
Storms, K., Kapraun, J., Rudolf, M., 2015. Can retail investor attention enhance market efficiency? Insights from search engine data. *Working Paper WHU*, 38.

White, A., 2018. Announcing the Coinbase Suite of Institutional Products. *Retrieved from: https://blog.coinbase.com/coinbase-institutional-deea317d23af*.

Yermack, D., 2015. Is Bitcoin a real currency? An economic appraisal. *Handbook of digital currency*, 31-43.

Appendix

Event 1: **Event date**: May 6, 2015
Event-specific cryptocurrency: Ripple
Event description: Ripple gets fined by the Financial Crimes Enforcement Network (FinCEN) for "willful violations" of the Bank Secrecy Act (BSA). The fine cost Ripple a total of 700,000 USD.
Source: https://www.coindesk.com/fincen-fines-ripple-labs-700000-bank-secrecy-act/

Event 2: **Event date:** January 20, 2016
Event-specific cryptocurrency: Dash
Event description: Lamassu announces that they will offer Dash as an alternative to bitcoin in their ATM project. This means that customers can now buy and sell Dash at the Cryptomats of Lamassu.
Source: https://cointelegraph.com/news/dash-to-become-the-first-alternative-to-bitcoin-offered-by-the-lamassu-atm-project

Event 3: **Event date:** September 15, 2016
Event-specific cryptocurrency: Ripple
Event description: Ripple raises 55 million US dollars from big banks including Standard Chartered, Accenture Ventures, SCB Digital Ventures, the venture arm of Siam Commercial Bank, and Japan's SBI Holdings
Source: https://www.cnbc.com/2016/09/15/google-backed-blockchain-start-up-ripple-raises-55-million-from-big-banks.html

Event 4: **Event date:** January 2, 2017
Event-specific cryptocurrency: Monero
Event description: One of the biggest cryptocurrency exchanges adds support for Monero (XRM), meaning that this currency can now be traded on this exchange
Source: https://blog.kraken.com/post/214/kraken-launches-monero-trading/

Event 5: **Event date:** January 10, 2017
Event-specific cryptocurrency: Ripple
Event description: One of the leading Europe-based bitcoin exchanges adds the ability to also trade Ripple (XRP) through its platform.
Source: https://www.reuters.com/article/us-blockchain-ripple/bitstamp-adds-ripple-currency-xrp-to-trading-platform-idUSKBN14V055

Event 6: **Event date:** March 10, 2017
Event-specific cryptocurrency: Bitcoin
Event description: The Securities and Exchange Commission (SEC) rejects the idea of Tyler and Cameron Winklevoss to launch a bitcoin ETF.
Source: https://www.forbes.com/sites/laurashin/2017/03/10/sec-rejects-winklevoss-bitcoin-etf-sending-price-tumbling/#48c5c2ff643c

Event 7: **Event date:** May 3, 2018
Event-specific cryptocurrency: Litecoin
Event description: Coinbase adds Litecoin as its third cryptocurrency to their website and mobile apps. Litecoin can now be bought, sold, send, and stored on Coinbase.
Source: https://techcrunch.com/2017/05/03/coinbase-adds-support-for-litecoin/

Event 8: **Event date:** May 16, 2017
Event-specific cryptocurrency: Ripple
Event description: Ripple locks up $14 billion worth of its cryptocurrency (XRP) into smart contracts, ensuring investors that none of the employees will flood the market with their share of the currency.
Source: https://www.coindesk.com/ripple-pledges-lock-14-billion-xrp-cryptocurrency/

Event 9: **Event date:** September 14, 2017
Event-specific cryptocurrency: Bitcoin
Event description: BTC China, a bitcoin exchange, halts the trading on their platform in anticipation of a total cryptocurrency ban by the Chinese government.
Source: https://www.scmp.com/business/companies/article/2111249/btc-china-halt-bitcoin-trading-amid-reports-blanket-ban

Event 10: **Event date:** November 9, 2017
Event-specific cryptocurrency: Dash
Event description: Dash v12.2 increases its block size, used to mine the cryptocurrency, from 1MB to 2MB.
Source: https://www.dashforcenews.com/dash-12-2-update-doubles-block-size-lowers-fees-bitcoins-segwit2x-fails/

Event 11: **Event date:** December 10, 2017
Event-specific cryptocurrency: Bitcoin
Event description: The first ever futures market for cryptocurrencies launches for bitcoin on the Chicago Board Options Exchange (CBOE).

	Source: https://news.bitcoin.com/heres-what-you-should-know-about-cboes-bitcoin-futures-launch/
Event 12:	**Event date:** January 30, 2018 **Event-specific cryptocurrencies:** Bitcoin, Ripple, Litecoin, Dash, and Monero **Event description:** Facebook bans all advertisements on its website involving ICOs or cryptocurrencies in general. **Source:** https://cointelegraph.com/news/facebook-bans-cryptocurrency-ico-ads-because-of-deceptive-promotional-practices
Event 13:	**Event date:** March 29, 2018 **Event-specific cryptocurrencies:** Bitcoin, Ripple, Litecoin, Dash, and Monero **Event description:** Five cryptocurrency exchanges in Japan shutdown their operation after not getting approved to be operating these exchanges by Japanese financial regulators. **Source:** https://news.bitcoin.com/cryptocurrency-exchanges-in-japan-throw-in-the-towel/
Event 14:	**Event date:** May 11, 2018 **Event-specific cryptocurrency:** Bitcoin **Event description:** The bankrupt cryptocurrency exchange Mt. Gox moves 8200 BTC from one of their wallets, indicating the former exchange might dump these bitcoins into the market. **Source:** https://www.ccn.com/8200-btc-moved-from-mt-gox-wallet-possible-sell-off-affects-bitcoin-price/

Table A: Overview of the events used in the event study methodology.