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Can Investor Attention Predict Cryptocurrency Returns?

On the interconnections of the cryptocurrency market

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Tiivistelmä :

Tämän tutkielman tarkoitus on tutkia kryptovaluuttojen tuottojen ennustettavuutta sijoittajien mielenkiinnolla, kryptovaluuttamarkkinoiden linkittyneisyyttä sekä mikä aiheuttaa huomiota kryptovaluuttoihin. Tämä toteutetaan tutkimalla Bitcoinia, Ethereumia ja Rippleä, jotka olivat markkina-arvon perusteella kolme isointa kryptovaluuttaa joulukuussa 2019.

Tutkimuksen data koostuu viikoittaisesta tuottodatasta, viikoittaisesta muutoksesta sijoittajien mielenkiinnossa, jota mitataan Google Trend datalla sekä viikoittaisesta muutoksesta viikon keskiarvo kaupankäyntivolyymissa. Tutkimus sijoittuu aikavälille 2016 – 2019. Empiirinen analyysi toteutetaan suorittamalla OLS regressio, VAR-malli sekä Granger-kausalisuustesti. Tulokset testataan jakamalla aikaväli kahteen osaan: ennen kryptovaluuttojen kuplaa sekä jälkeen kryptovaluuttojen kuplan, sekä lisäämällä kaikkien kryptovaluuttojen sijoittajien mielenkiinto mittari regressioon.

Tutkimuksen tulokset osoittavat, että markkinoiden vaihe vaikuttaa tuottojen ennustettavuuteen, sillä positiivinen tilastollinen merkittävyys katoaa jälkimmäisellä ajanjaksolla Bitcoin ja Ethereum malleissa, mutta säilyy Ripplellä molemmilla ajanjaksoilla. Tämä vahvistaa aikaisempia tutkimustuloksia markkinoiden tehostumisesta markkinoiden kypsyessä.
Tutkimus löytää tilastollisesti merkittäviä todisteita kryptovaluuttamarkkinoiden linkittyneisyydestä, sillä Ripplen sijoittaja mielenkiinto kykenee ennustamaan tuottoja kaikille tutkimuksen kryptovaluutoille koko ajanjaksolla. Valumavaikutus kryptovaluuttojen välillä ei ole välitön, mikä vahvistaa aikaisemmat tutkimustulokset. Tämän lisäksi tutkimus avaa laumamentaliteetin välittymistä markkinoille sijoittajamielenkiinnon kautta. Sijoittaja mielenkiinnon osoitetaan johtuvan kryptovaluutan omista tuotoista sekä Bitcoinin tuotoista. Tutkimuksen tulokset avaavat kryptovaluuttamarkkinoiden linkittyneisyyttä, markkinoiden dynamiikan jatkuvaa muutosta sekä kryptovaluuttojen tuottojen ennustettavuutta sijoittaja mielenkiinnolla.

KEYWORDs: Investor attention, Investor sentiment, Cryptocurrency, Behavioral finance

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1 Introduction

Cryptocurrencies have gained much notice as a financial asset during recent years in the media as also in academic research. Bitcoin´s price development in years 2016 to 2017 was compared to the tulip mania, which made Bitcoin known around the world. Cryptocurrencies differ from other currencies as they are peer-to-peer electronic cash systems which do not go through a financial institution, for example, banks. Due to their nature, they are not thus affected by authorities, have no physical representation and are infinitely divisible. Contrary to other financial assets, they do not have any intrinsic value as their value is based on the security of an algorithm which can trace all transactions. (Corbet, Lucey, Urquhart, & Yarovaya 2019.)

The cryptocurrency market differs from the traditional financial markets due to its nature as well as its behaviour. It has been shown to have higher returns and volatility (Baur, Hong & Lee 2018), withholding significant financial risk, having significant fluctuations even without price bubbles (Fry 2018), and being prone for pricing bubbles (Fry 2018; Corbet, Lucey & Yarovya 2018; Cheung, Roca & Su 2015; Cheah & Fry 2015; Fry & Cheah 2016). It is not correlated with other traditional asset classes in normal market conditions (Bauer et al. 2018), and it is not affected by shocks to traditional financial markets (Corbet, Meegan, Larkin, Lucey & Yarovaya 2018). Despite these factors, it does not act as a safe haven, as it is rather a diversifier (Corbet et al. 2019). Further, the extreme market conditions caused by Covid-19 pandemic showed that Bitcoin can co-move with the US stock markets (Grobys 2020). As a young asset class cryptocurrency market has been shown to mature by time and market turmoil as it has become more efficient with time (Tran & Leivik 2019; Vidal-Tomás & Ibañez 2018; Urquhart 2016; Kyriazis 2019). Further, the cryptocurrency market is highly interlinked, and the connections between cryptocurrencies are time-dependent (Corbet et al. 2018; Ji, Bouri, Lau, & Roubaud 2019; Ferreira & Pereira 2019).

Drivers of cryptocurrency returns and pricing have been a widely studied field of the cryptocurrency literature (Corbet et al. 2019). Shen, Urquhart and Wang (2019) suggest a factor model for explaining cryptocurrency returns as Hayes (2017) derives the price formulation of cryptocurrencies via technical aspects. As Kristoufek (2015) and Sovbetov (2018) combine technical aspects and cryptocurrency-related data showing that cryptocurrency market behaves under traditional monetary fundamental factors in long-term. As in short-term investor attention, volatility, trading volume, and price trends affect the prices. Sovbetov (2018) shows that investor attention travels slowly within the market in long-term periods. The interlinkedness of the cryptocurrency market and speculative nature is also shown lead to herding during turmoil events in the cryptocurrency markets (Bouri, Gupta & Roubaud 2019; Vidal-Tomás, Ibáñez, Farinós 2019; Kallinterakis & Wang 2019). The results vary for the driver of the herding between larger cryptocurrencies (Vidal-Tomás et al. 2019) and smaller cryptocurrencies (Kallinterakis & Wang 2019).

Due to their nature cryptocurrencies are almost impossible to value using fundamental analysis. In contrast to the traditional finance theory, behavioural finance allows for irrational behaviour and relies on two different building blocks: Limits to arbitrage and Cognitive psychology (Barberis & Thaler 2003). As the cryptocurrency market has been shown to be affected by noise and is highly speculative also lacking efficient markets for arbitrage, behavioural finance could offer explanations for the behaviour of the market. In the field of behavioural finance, investor sentiment has been shown to have abilities to explain the price deviations and valuations of highly speculative assets (Baker & Wurgler 2007). Thus, it is not far-fetched to suggest that it plays a role in the fluctuation of cryptocurrencies as in valuation (Eom, Kaizoji, Kang & Pichl 2019). Investor sentiment does not have any clear definitions; for example, Baker and Wurgler (2017) define it as “propensity to speculate”. Due to this, there is not a single proxy for investor sentiment. Investor sentiment can be measured by following certain investors, deriving it from market data, using a composite sentiment index and utilizing many other statistics and data. (Klemola, Nikkinen & Peltomäki 2016.) This study utilizes investor attention as a proxy for investor sentiment using the Google Trends data, which is supported by earlier literature (Kristoufek 2013; Eom et al. 2019; Urquhart 2019).

The earlier literature about the effects of investor sentiment to cryptocurrencies differ between studies due to varying investor sentiment proxies, different time samples, different cryptocurrency samples, and different methods. One of the first studies on the topic, Kristoufek (2013), studies the effect of investor sentiment to Bitcoin finding statistically significant predictive power. Similar results are found for Bitcoin and other cryptocurrencies by Nasir, Huynh, Nguyen and Duong (2019), Subramaniam and Chakraborty (2020), Karalevicius, Degrande, Weerdt (2018), and Gurdgiev and O'Loughlin (2020). As Shen, Urquhart and Wang (2019), Bleher and Dimpfl (2019a), Urquhart (2018), and Eom et al. (2019) do not find statistically significant predictive powers.

This thesis studies the prediction abilities of individual investor attention of Bitcoin, Ethereum and Ripple to their returns. As investor sentiment has been shown to have spill-over effects in traditional financial assets (Audrino & Tetereva 2019) the analysis is conducted by analysing all of the three investor attentions prediction abilities cross-wide the returns of cryptocurrencies. To unfold the market dynamics of cryptocurrencies, the investor attention proxies are also studied by predicting the investor attention changes by cryptocurrency returns and individual trading volumes.

1.1 Purpose of the study

The purpose of this thesis is to study the effects of investor sentiment to the returns of Bitcoin, Ethereum and Ripple, to examine the interlinkedness of these three cryptocurrencies, and to study what causes attention to these three cryptocurrencies. The selection of these three currencies is motivated by their market capitalization as they were the three biggest cryptocurrencies by market capitalization in December 2019 (https://www.coinmarketcap.com). This thesis uses the Google Trends data as a proxy for investor attention to capturing the investor sentiment for individual cryptocurrency and test if it has an impact on near-term future returns. Kristoufek (2013) finds that the

“Bitcoin” search queries have an impact on future returns in Bitcoin. Hence, the first hypothesis is:

H1: Investor attention has an impact on returns for Bitcoin, Ethereum and Ripple

In addition, possible spillover effects from investor attention to the returns of other cryptocurrencies are tested. Prior literature about investor sentiment has shown that there are spill-over effects on investor sentiment between industries (Audrino & Tetereva 2019). Also, studies about cryptocurrencies have shown that the markets are interlinked and the returns spill-over between cryptocurrencies (Corbet et al. 2018; Ji et al. 2019; Ferreira & Pereira 2019). Corbet et al. (2018) and Ji et al. (2019) propose that Bitcoin dominates the market as a shock sender, but the findings of Zięba, Kokoszczyński, and Śledziewska (2019) are in contrast with these results. Further, the interlinkedness of the cryptocurrency market has been shown to be time-dependent (Ji et al. 2019; Ferreira & Pereira 2019). Due to this, it is interesting to study if investor attention from one cryptocurrency affects another´s returns. The second hypothesis is:

H2: Individual cryptocurrency investor attention has a spill-over effect on other cryptocurrencies´ returns

To understand better how the cryptocurrency market behaves, it is essential also to understand what affects the investor attention of cryptocurrencies. Earlier studies have shown that the relationship between Bitcoin´s returns and investor sentiment is bidirectional as past returns increase the sentiment and vice versa (Kristoufek 2013). To extend the literature, this study examines what affects the investor attentions of Bitcoin, Ethereum and Ripple the third hypothesis being:

H3: Returns and volume has an impact on individual investor attention

This thesis contributes to the previous literature by studying the effects of investor sentiment on cryptocurrency returns using more recent time-series as also extends the literature about cryptocurrencies by studying Ethereum and Ripple as the literature has mostly focused on Bitcoin. This thesis also adds some novelty to the literature about cryptocurrencies as to the knowledge of writer there has not been studies about the spill-over effects of investor sentiment in the cryptocurrency market using other currencies investor sentiment than Bitcoin´s. In addition, it studies what affects the investor sentiment of individual cryptocurrencies unfolding the market dynamics and possible drivers of returns.

1.2 Structure of the study

The structure of the thesis is the following: The first chapter introduces the study and layouts the hypotheses. The second chapter explains cryptocurrencies and their market behaviour. The third chapter introduces behavioural finance, as the fourth chapter moves into investor sentiment and reviews previous literature about investor sentiment and cryptocurrencies. The fifth chapter coverages the data and methodology. In the sixth chapter, the empirical results are discussed. The last chapter concludes the study and suggests future research ideas on the topic.

2 Cryptocurrencies

In recent years, cryptocurrencies have gained the attention of investors, regulators, media and governments. It can be said as certain that almost everyone in the developed world heard about cryptocurrencies during the years 2016-2017 when the Bitcoin surged and attracted numerous new investors. The Bitcoin was firstly presented by Nakamoto (2008), being the world´s first cryptocurrency. Cryptocurrencies are separated from our traditional investment assets and currencies as they are not associated with financial institutions or higher authorities. The essence of cryptocurrencies is to be a peer-to-peer electronic cash system operating through online payments. Unlike most other financial assets in the financial markets, cryptocurrencies do not have an intrinsic value as the value is not based on any tangible asset, firm or countries economy. Further, Cheah and Fry (2015) conclude in their study that Bitcoin´s fundamental price is zero. The popularity of cryptocurrencies can be associated with its core nature: low transaction costs, government free design, and peer-to-peer transactions. The surge of cryptocurrencies can be seen in the trading volumes, prices, volatility, media attention, and academic attention. (Corbet et al. 2019).

2.1 History, dilemmas and differences in cryptocurrencies

The first cryptocurrency, Bitcoin, was introduced in 2008 and as of today, it is still the largest and most-known cryptocurrency in the world. As of 29th of December 2019, the three biggest cryptocurrencies by market capitalization were Bitcoin, Ethereum and Ripple having a total market capitalization of approx. $157 804 million, Bitcoin being the biggest ($134 570 million) followed by Ethereum ($14 698 million) and Ripple ($8 536 million). The whole cryptocurrency market capitalization is $196 776 million. During years 2016-2017, Bitcoin faced a surge in prices that can be compared to the tulipmania, at its highest the market capitalization climbed up to $326 711 million. The significance of Bitcoin of the cryptocurrency market transfers to the academic studies as most studies focuses on Bitcoin (Corbet et al. 2019).

Corbet et al. (2019) present a trilemma for the cryptocurrencies that slows down the development of cryptocurrencies. The interlinked trilemma is made of 1) potential for inherent bubbles 2) regulatory alignment 3) cybercriminality. If cryptocurrencies have inherent price bubbles, it creates an attraction for cybercriminality, which calls for the need for regulatory alignment. Regulatory alignment has been a cause for significant fluctuations to the price of bitcoin, and stabilization of regulation could lead to significant soars in the valuations of cryptocurrencies. Cybercriminality is also a significant player to the instability of cryptocurrencies affecting the price fluctuation.

The inherent bubble dilemma has been shown by Corbet et al. (2018) and Cheung et al. (2015) who both find that Bitcoin experiences short-term bubbles in its price development. Similar results were found by Cheah and Fry (2015) who suggest that Bitcoin prices withhold speculative bubbles and it is instead a speculative asset than a currency. In addition, Fry and Cheah (2016) show that Bitcoin and Ripple exhibits a negative bubble from 2014 onwards. Interestingly, Fry (2018) shows that when taking into account the heavy-tails and liquidity risks, Bitcoin and Ethereum exhibits bubbles, but Ripple does not. Thus, there is no consensus for the bubble dilemma for Ripple.

Chen and Hafner (2019) study the bubble formation in cryptocurrencies using sentiment measure as a transition variable in a smooth transition autoregression. They use as a proxy for investor sentiment a sentiment index which is formed by analysing a social media platform Stocktwits´s messages. They use the CRIX index that is a value-weighted cryptocurrency market index for measuring the returns for the cryptocurrency market. Their results show that cryptocurrency markets are prone to bubbles and have a leverage effect. Leverage effect means that bad sentiment or bad news increase volatility. Adding that the cryptocurrency market can be seen explicitly driven by the sentiment index. In contrasts, Grobys (2019) shows in his paper about Bitcoin and Ethereum that these two cryptocurrencies do not possess asymmetries in their volatility processes.

The regulatory alignment raises massive problems for governments and regulators as the purpose behind cryptocurrency is to be free from authorities or institutions. In addition, recent financial literature has not been able to define clearly is it a currency or a financial asset. Further, the cryptocurrency market withholds numerous different cryptocurrencies which differ from each other and are not domiciled inside any single country´s borders. Adding to the base nature of cryptocurrencies, the cybercriminality involved to them poses a massive international regulation problem. This regulation lack can be seen to affect the prices of cryptocurrencies as possible actions from Japan, China and South Korea had a strong negative influence to the price of Bitcoin in the turn of 2017 and 2018. (Corbet et al. 2019)

The cybercriminality dilemma can be divided broadly into two components: 1) Crimes arising from using cryptocurrencies, and 2) Cybercrimes affecting the structures of cryptocurrencies. Often cited argument about cryptocurrencies is that they are used for illegal activities, usually as a payment method or for money laundering (Kristoufek 2015). A good example is the Silk Road which was a market place for drugs on the dark web. After closing the site, the FBI estimated that 5% of the bitcoin economy could be accounted to the Silk Road. As an online-based technology, cryptocurrencies are vulnerable to cybercrimes. Often sited cybercrimes are hackings of Initial Coin Offerings (ICOs), exchanges and cryptocurrency wallets. (Corbet et al. 2019) Grobys (2019) showcases the societal impact of the cryptocurrency hackings by noting that during the years 2013-2017 twenty-nine Bitcoin hackings occurred which accumulated to $8,7 billion in losses when calculated using the average price for the Bitcoin in the year 2018.

Cryptocurrencies have different uses and purposes. This thesis focuses on Bitcoin, Ethereum and Ripple; thus, we concentrate on the differences between these three cryptocurrencies. It can be stated that cryptocurrencies rely on the trust of the users and are ultimately depended on the blockchain technology. Bitcoin was developed as an alternative to the current Fiat money system as Ripple (Currency noted as XRP) was developed as a medium of exchange and as a distributed payment system (Fry & Cheah

2016). Ethereum differs from the former two as it is a decentralized open-source blockchain system having its own cryptocurrency Ether (noted as ETH). It can be used as a platform for other cryptocurrencies as well as for decentralized smart-contract settlements.

2.2 Characteristics of Cryptocurrency market

As formerly noted, there is not a single consensus in the academic financial world about the asset class of cryptocurrencies (Fry & Cheah 2016). However, recent studies are inclining towards that they are speculative assets (Baur et al. 2018; Baek & Elbeck 2015) rather than currencies and an asset class of their own (Corbet et al. 2018). Bitcoin is shown to have higher return and volatility than numerous other assets and that it experiences significant negative skewness as well as high kurtosis compared to other assets (Baur et al. 2018). The cryptocurrency market withholds an inherent significant financial risk and is prone for major fluctuations even without price bubbles (Fry 2018). Taking into account that the literature shows significant proof for bubbles in cryptocurrency market (see Fry 2018; Corbet et al. 2018; Cheung et al. 2015; Cheah & Fry 2015; Fry & Cheah 2016) it is reasonable to state the cryptocurrency market is highly risky and speculative by its nature.

Corbet et al. (2018) show that the cryptocurrency market is highly interlinked. In addition, their results suggest that the price development of Bitcoin has been a driver for the price development of Ripple. Showing evidence that the relationship is unidirectional and Bitcoin driven. Similar results are found by Ji et al. (2019) who use a broader data set (cf. Corbet et al. 2018) and segregate the return spillovers between positive and negative returns. Their results show that Bitcoin and Litecoin are the centers of the cryptocurrency market, sending most significant shocks to other cryptocurrencies. However, it is shown that the integration of cryptocurrency markets is time-dependent and the results suggest that after April 2017 Bitcoin has been a net receiver showing that the dominant position of Bitcoin might be disappearing by time. As per traditional finance studies, negative shocks are stronger than positive shocks. It is also shown that

Ripple and Ethereum seem to be disconnected from each other, offering potential for diversification. Further, Ethereum is shown to be a recipient of shocks rather than a sender of shocks showing that bigger and smaller cryptocurrencies dominate it.

In contrast to the results of Ji et al. (2019), Ferreira and Pereira (2019) suggest that after the crash of the Bitcoin, the cryptocurrency markets are more integrated than in the pre-crash period. They conclude that other cryptocurrencies seem to be more contagious to Bitcoin in the post-crash period. Using Minimum Spanning tree technique and Vector autoregression Zięba et al. (2019) find that Bitcoin is not a dominant price shock sender or receiver (cf. Ji et al. 2019) instead it is a separate entity of the market. They explain their findings by the technical aspect of mining, leading to a conclusion that smaller cryptocurrencies that are more efficient to mine can better answer to demand shocks due to more evenly distributed supply side. Even though Bitcoin did not have many relationships between other cryptocurrencies, they were able to identify relationships between other cryptocurrencies.

Baur et al. (2018) compare Bitcoin to 16 other assets founding no evidence for correlation between Bitcoin and other assets showing that Bitcoin is different from the traditional assets. Similar results are found by Corbet et al. (2018) using Bitcoin, Litecoin and Ripple as data for cryptocurrencies. Their results show that the cryptocurrency market seems to be isolated from the rest of the market and unaffected by shocks in the traditional financial markets.

As cryptocurrencies are not linked with the traditional assets, they might be a potential save haven during turmoil events in the financial markets. However, recent studies have shown that this is not the situation (Baur et al. 2018). Bouri, Molnár, Azzi, Roubaud and Hagfors (2017) find similar results, the only exception being a hedge against the extreme market movement in the Asian stock market and a diversifier for most other assets. In contrast to these results, Grobys (2020) shows that Bitcoin and S&P500 comove during the Covid-19 pandemic showing evidence that it does not serve as a hedge during extreme market situations. To summarize the citations from the review of empirical literature of cryptocurrencies by Corbet et al. (2019), it can be stated that cryptocurrencies act more of as diversifier rather than a safe haven.

2.2.1 Cryptocurrency market efficiency

As a highly speculative and risky asset, cryptocurrencies might exhibit inefficiencies in their market dynamics. In recent literature, cryptocurrencies market efficiency has been one of the most studied aspects of cryptocurrencies (Corbet et al. 2019). In a survey of the market efficiency literature about cryptocurrencies, Kyriazis (2019) summarizes the findings of numerous papers by stating that overall results suggest that the cryptocurrency market is inefficient. However, long-range dependence seems to fade out as the cryptocurrencies mature by passing time.

One of the firsts to study the efficiency was Urquhart (2016) who studied the weak market efficiency of Bitcoin using numerous methods. Urquhart (2016) shows that Bitcoin is inefficient. However, he is able to show that in the latter half of the sample (8/2013-7/2016) Bitcoin became more efficient, predicting that as the market matures and attracts more investors the market becomes more efficient by time. The results of Charfeddine and Maouchi (2019) are in agreement with the results of Urquhart (2016) as they show that Bitcoin, Litecoin and Ripple all experience long-range dependence in their prices showing inefficiency in the prices. Interestingly, they find that Ethereum seems to be efficient. Tran and Leivik (2019) apply a bigger and longer data set (4/2013-2/2019) including five cryptocurrencies (Bitcoin, EOS, Ethereum, Ripple and Litecoin). Their results agree with the findings of Urquhart (2016) and Kyriazis (2019) as they derive a measure for the level of Adjusted Market Inefficiency Magnitude which shows that the included cryptocurrencies have experienced significant inefficiencies in the past but became mostly efficient after 2017. Studying the semi-strong market efficiency of Bitcoin in the Bitstamp and Mt. Gox markets, Vidal-Tomás and Ibañez (2018) show that Bitcoin has become more efficient during the time to its own news. In contrast, monetary policy news does not affect Bitcoin. Caporale, Gil-Alana and Plastun (2018) find similar results (see Urquhart 2016; Tran & Leivik 2019; Vidal-Tomás & Ibañez 2018) as they show that returns are persistence but are becoming more efficient.

Using intraday data and segregating between bull and bear period (breakpoint 17th January 2018) Zhang, Chan, Chu and Sulieman (2020) show that the hourly returns do not meet the prerequisites of an efficient market using classical methods. In contrast, using a rolling DFA Hurst exponent test, they find that the markets are efficient during bull regime but show persistence positive autocorrelation behaviour during bear regimes. Suggesting that cryptocurrency markets are more efficient during the bull market. In addition, they show that the market becomes more liquid for Bitcoin during a bear market regime, as Ethereum and Litecoin become less liquid. Baur et al. (2018) show that Bitcoin experiences autocorrelation and could offer significant returns for momentum traders. In contrast, Grobys and Sapkota (2019) find that cryptocurrencies do not offer any significant excess returns to momentum traders using numerous different momentum strategies. Signaling that the cryptocurrency market is efficient. As the results differ between studies, there is no clear consensus for the efficiency of the cryptocurrencies.

2.2.2 Cryptocurrency pricing

As cryptocurrencies do not possess any intrinsic value, the pricing of cryptocurrencies possesses interesting questions for academics and market participants. What are the drivers of the prices and are they based on fundamentals, or is it mostly white noise? The relationship between investor sentiment and cryptocurrencies is studied in later chapters.

One of the first studies to answer this question is Kristoufek (2015) who tries to find the main drivers of Bitcoin prices. Using a wavelet coherence approach, he studies the most often claimed drives of the Bitcoin prices. Bitcoin prices seem to behave under traditional monetary fundamental factors (usage in trade, money supply and price level) in the long-run but deviate away in the short-run periods. As miners provide the supply side of Bitcoin, it would make sense that rising prices attract more miners for obtaining profits. This is shown to be true, but the effect is found to vanish during time as the technical aspects have driven the hash rates and difficulty too high. As a speculative asset, investor interest could be one of the key factors for the pricing. The relationships are clearly seen in the long-run, and in the short-run, it can be seen to push the prices further up in the rising market and vice versa.

Shen, Urquhart and Wang (2019) propose a three-factor pricing model mimicking the pricing models of traditional financial assets. Citing the findings of Grobys and Sapkota (2019) and the fact that smaller cryptocurrencies tend to outperform bigger ones they suggest using reversal and size effects as factors combined with a market factor leading to a model:

$$r_{i,t} - Rf_t = \alpha + \beta_{i,1} RMRF_t + \beta_{i,2} SMB_t + \beta_{i,3} DMU_t + \varepsilon_t \quad (1)$$

where $r_{i,t}$ is the weekly return, $RMRF_t$ is the excess return on the market, SMB_t is the size factor and DMU_t is the reversal factor. The reversal factor is constructed by using 1-1 strategy buying the loser portfolios and selling the winner portfolios of the last week. Their results show that the size-reversal portfolio creates statistically significant returns when buying the smallest and biggest losers and selling the largest and biggest winners. Their suggested model outperforms the simple cryptocurrency CAPM model and shows significant evidence for the capability of explaining cryptocurrency returns better than a simple cryptocurrency CAPM model.

Taking a different approach Hayes (2017) studies 66 different cryptocurrencies denominated in Bitcoin using a regression model for solving the biggest factors affecting the price of cryptocurrencies. The study approaches pricing process from a technical background. The cross-section regression results show that computational power, rate of coin production and the relative hardness for mining are statistically significant factors for explaining the pricing of cryptocurrencies. The results are in, somewhat, contrast with the financial studies as they tend to take given that cryptocurrencies do not exhibit any fundamental/intrinsic value. However, the results of Hayes (2017) suggest that the cost of production drives the value and pricing of cryptocurrencies.

Sovbetov (2018) cites Poyser (2019), suggesting that cryptocurrencies pricing is affected by internal and external factors. Internal factors being supply & demand raising from the technical aspects, as the external factors are divided into three different factors: crypto market, Macro-financial and political. Sovbetov (2018) studies mostly which crypto market factors and Macro-financial factors affect the pricing formation using an ADLR approach. His results show that the cryptocurrency market is affected by its own volume and volatility as the price trend as well. It is shown that attention is also a significant factor in long-term time periods suggesting that attention or attraction travels slowly within the market. The Macro-financial factors do not show to have any meaningful effect on the price formation of cryptocurrencies; however, SP500% has some relationships with Bitcoin.

Bouri et al. (2019) study herding in the cryptocurrency market. Herding arises from noise trading when numerous investors are trading based on white noise at the same time. This is often caused by fear of missing out that takes place often in the biggest turmoils. Taking into account the base nature of cryptocurrencies (High volatility and speculative nature), it is reasonable to suspect that herding is significant in the cryptocurrency markets. Their results show that cryptocurrency market experiences herding behaviour varying through time which is shown to grow during uncertainty. These results align with the results of Vidal-Tomás et al. (2019) who find that the herding is more prominent during down-markets. Further, they show that the main driver of the cryptocurrency markets are the returns of the largest cryptocurrencies, not just Bitcoin´s returns.

Similar results are found by Kallinterakis and Wang (2019) who study herding in the cryptocurrency market, taking into account the movement of the market, volatility and trading volume. Their results show evidence for herding behaviour which is asymmetric, prominent during up-markets, low volatility and high-volume days. Even though Bitcoin is often seen as the market driver for the cryptocurrency market, the herding arises from the smaller cryptocurrencies herding towards larger ones.

3 Behavioural finance

The academic interest started to gradually shift from the efficient market hypothesis (EMH) and its fundamentals in the 1990s towards human psychology and its relation to the financial markets. The gradual shift was launched by the growing sentiment that the theoretical models did not capture all vital fluctuations in the financial markets (Shiller 2003). The main hypothesis in behavioural finance is that the assumption about perfectly rational investors do not apply as humans act irrationally. These irrational acts are tried to interpret and explain by using human psychology. Behavioural finance has step by step gained more attention in the academic field in recent years. The founder of efficient market hypothesis Fama (1998) criticizes behavioural finance on two main points: anomalies are caused evenly by over- or underreaction, and anomalies tend to disappear from the market as time passes or the methodologies improve. The first argument is debunked by Shiller (2003) by stating that the criticism arises from a misunderstanding of behavioural finance as over- or underreaction does not always occur if there is no fundamental psychological principle for it. Further, he states that the disappearing or switching of anomalies does not lead to a fully rational market and that it is natural for academic research that newer studies replace older studies.

Behavioural finance is often divided into two building blocks: limits to arbitrage and psychology (Barberis & Thaler 2003). The next chapter unfolds the psychology behind behavioural finance as one after that focuses on arbitrage.

3.1 Biases and irrational behaviour

Behavioural finance mostly relies on cognitive psychology which studies patterns in decision making. These patterns display systematic errors behind decision making. Behavioural finance aims to explain irrationalities and anomalies in the market by these findings. However, not all deviations from fundamental prices are caused by irrational decision making, as some are temporary imbalances in demand and supply. (Ritter 2013)

Perhaps one of the most prominent biases in the financial markets is overconfidence. Overconfidence refers to the situation when a decision-maker overestimates their own knowledge. Overconfidence is more visible and severe in the fields where tasks require judgement, and the feedback from decisions is delayed, these factors very much applying to the financial markets (Daniel, Hirshleifer & Subrahmanyam 1998). Overconfidence may lead to excessive trading, riskier portfolios and relying too much on own price estimates, these issues leading to lower expected utility for overconfident investors (Odean 1998).

Self-attribution bias can be seen as an origin and a booster for overconfidence. Self-attribution bias refers to the situation when a person takes success as a sign of his own skills and losses are due to bad luck or other external reasons. A good example of this is the situation when an investor who uses private information (own studies etc.) gains a confidence boost when public information is in line with his own studies, as public information which disagrees does not lead to commensurate loss of confidence. Overconfidence and self-attribution bias can be seen as a source for momentum, and post-earnings announcement as signs of success drifts prices further away from fundamental value, eventually drifting back to the fundamental value due to more public information. (Daniel et al. 1998.)

When making decisions basing on stereotypes, decision making is biased by representativeness. More formally defined by Kahneman and Tversky (1972) as a person who: “evaluates the probability of an uncertain event, or a sample, by the degree to which it is: (i) similar in essential properties to its parent population; and (ii) reflects the salient features of the process by which it is generated.” Representativeness bias may lead to misattributing good traits of a company as traits of a good investment, and taking past returns as an indicator for future returns and thus preferring recent winners, thus acting under extrapolation bias (Chen, Kim, Nofsinger & Rui 2007; De Bondt, 1993; Dhar & Kumar 2001).

Representativeness may also lead to overweighting recent events or data which may lead to taking recent events as a new norm (Ritter 2013). Another outcome may be trend-chasing when investors believe that trends have systematic causes; this can also be called hot hands effect. Not understanding how randomness or probabilities work may also lead to gambler´s fallacy. Gambler´s fallacy means that if in an independent sample, an outcome occurs the possibility for the next outcome to be different outcome increases. (Hirshleifer 2001.) Gambler´s fallacy and hot hands effect can be seen in the financial markets as Andreassen and Kraus (1990) show that in normal market conditions rises usually lead to an increased amount of sell trades as dips lead to an increased amount of buy trades. However, greater magnitudes of changes, trends in prices, lead to more trend-chasing.

Conservatism bias can be seen as an opposite force to representativeness bias. Conservatism bias occurs when market participants are slow to update their views based on new information; in other words, they anchor to old information (Ritter 2013). This leads to underreaction and can thus be seen as an explanation for underpricing (Chan, Frankel & Kothari 2004). Further, conservatism can be seen as a factor for momentum as analyst do not update their earnings estimates enough after new information occurs, anchoring to the old information (Shefrin 2002:20,35). An explanation for when repressiveness or conservatism occurs by Barberis and Thaler (2003) states that people overreact to data if it is representative to an underlying model and underreact when not. Hirshleifer´s (2001) explanation follows the same lines as he suggests that conservatism is due to information costs. Information that requires cognitive costs is weighted less than information which does not require as much cognitive costs.

Herding is a phenomenon where humans copy the actions of others despite their own view and information. Herding can be seen to be caused by fear of deciding against others in fear of being criticized after being wrong alone. Another reason for herding may be ”sharing-the-blame” effect which means that when all are wrong, it is not perceived as bad as being wrong by yourself. Herding amplifies stock market fluctuation as market participants sell when others are selling and vice versa, leading to excessive market volatility. (Scharfstein & Stein 1990.)

Kahnemann and Tversky (1979) present an alternative model to the expected utility theory, prospect theory. The key elements of prospect theory can be divided into three parts: decisions are measured as changes in wealth, not the final state, gained value decreases as the magnitude rises, applying to gains and losses, and the value gained from x monetary gain is not as much as the value lost for x monetary loss. These three elements are called: reference dependence, diminishing sensitivity and loss aversion (Tversky & Kahneman 1991). Barberis, Huang and Santos (2001) find that loss aversion relates to earlier performances, as losses do not affect as much in the presence of earlier gains as earlier losses make investors more loss averse.

3.2 Limits to arbitrage

If all of the market participants are rational, all stock prices should reflect their fundamental value at all moments. The fundamental value being a present value of all of the future cash flows for the firm. Moreover, if any price deviations occur ”money-hungry” arbitragers instantly arbitrage them for riskless profit. This is the simplified basis of the Efficient Market Hypothesis (EMH). It relies on the premise that if there are some misvaluations, they are fixed instantly by rational investors who are called arbitrageurs. Behavioural finance claims that even though the market is full of rational investors, the possible deviations from fundamental value may not be arbitraged away as arbitrage may be risky and costly for the arbitrager. This is in contrast to the well-known theories of finance (EMH, CAPM, and APT), which rely on the premise that arbitrage is risk-free, free, and possible for all investors. In reality, arbitrage requires capital and includes risk. (Shleifer & Vishny 1997; Barberis & Thaler 2003.)

The easiest risk to understand is the fundamental risk. Fundamental risk arises from the firm-specific fundamental changes during arbitrage. This risk can be hedged by substitute security that mimics the actual company. However, there is not often a perfect substitute leaving some fundamental risk to the arbitrageur, and there is always a possibility for news which do not affect any other company´s fundamental value. (Barberis & Thaler 2003.)

Barberis & Thaler (2003) present as a second limit to arbitrage implementation costs. Implementation costs arise from, for example, costs of shorting, commissions, bid-ask spreads, price impact and the information costs for arbitrage. To summarize, implementation costs withholds all costs that arise from the arbitrage position. These costs lead to smaller profits and thus make arbitrage positions less attractive. In addition, they note that not all market participants are allowed to short, which adds legal constraints to the limits of arbitrage.

Shleifer and Vishny (1997) state that in the real-world capital and the persons completing arbitrage are separated. This leads to an agency problem as the side with the capital may end the arbitrage position if the position does not earn profits straight away. This limit to arbitrage is named as performance-based arbitrage. Performance-based arbitrage restricts the side implementing the arbitrage strategy as they might take less aggressive positions against mispricings. Further, it may lead to more cautious arbitrageurs as they might avoid some initial actions due to the uncertainties of the future. The uncertainties are thought to be caused by noise traders, who are defined as irrational traders. In some situations, the mispricing may be driven further by noise trader sentiment which may lead to liquidated arbitrage positions and big losses for arbitrageurs as the price is driven further away from the fundamental price and the arbitrageur does not have enough capital to sustain the arbitrage position. This phenomenon may lead to less efficient financial market as prices may not recover to the fundamental value in extreme situations leading to notation that arbitrageurs may avoid arbitrage positions in extremely volatile situations (Shleifer & Vishny 1997). This risk can also be called noise trader risk (Barberis & Thaler 2003).

3.3 Noise trading

Black (1986) defines noise as ”emphasis on a diversified array of unrelated causal elements to explain what happens in the world”. Noise thus referring to all elements that deviate prices from the fundamental value. Further, he defines noise traders as traders who trade without information relying on noise as relevant information when they would be better off with not trading. Another definition for noise traders is traders that have a false belief of obtaining meaningful information from stockbrokers, technical analysis, consultants etc. or overconfidence driven traders who rely too much on their own ability to create a portfolio, in both cases leading to a portfolio created on false beliefs (De Long, Shleifer, Summers & Waldmann 1990). Even though noise traders create mispricing to the financial markets, they also make the market more liquid by trading on noise, making the market at the same time more efficient and inefficient (Black 1986).

Noise traders transfer noise to prices by trading on noise. When the noise inflates, the price drifts further away from the fundamental value cumulatively (Black 1986). As the noise inflates more rational investors take the opposite position to noise traders or grow their current position trying to take advantage of the noise traders by robust analysis (Black 1986; De long et al. 1990). However, as the prices deviate further away from the fundamental value the positions of rational investor grow as the noise trade risk grows which may create a ceiling for the rational investors as every rational investor has a risk limit (Black 1986). The same finding is shown by De long et al. (1990) who argue that arbitrageurs are risk-averse without infinite time horizons leading to an unwillingness to take a position against noise traders. Further, as the noise trader risk grows, the noise traders create more profits to themselves by bearing their own risk premium.

Numerous studies have shown that noise traders exist in the financial market. Barber, Odean and Zhu (2009), show that the irrational investors´ decisions strongly correlate with each other’s. The decisions being driven by psychological biases. Proving that the trading based on noise is systematic and thus can be seen in the asset prices. De long et al. (1990) hypotheses that assets with higher fundamental risk are affected more by the noise. This is backed up by the notion that noise traders rely more on their own analysis and noise, and are thus more interested in assets that leave much room to speculate. Together with the assumption that noise traders underestimate risk and overestimate return, it can be seen that speculative, risky assets include more noise trader risk than less risky assets.

4 Investor sentiment

Investor sentiment can be said to represent the feeling of the market. As the recent years have shown significant fluctuations in the markets, investor sentiment studies have gained more attention as market participants are trying to find reasonable explanations for the fluctuations. In contrast to the Efficient market theory, the moods of investors have been recognised to have an effect as early as 1936, when Keynes (1936: 157) said that “He who attempts to invest basing on genuine long-term expectation must surely run greater risks than he who tries to guess better than the crowd how the crowd will behave”. By understanding how sentiment affects the financial markets, we gain valuable information: Which biases in the financial markets affect the forecasts of investors and how it is possible to exploit these biases (Fisher & Statman 2000).

Barberis, Shleifer, and Vishny (1998) describe investor sentiment as “how investors form beliefs”, whereas Baker and Wurgler (2006) explain it as a “propensity to speculate”. Despite the missing of a single definition, behavioural finance studies hypotheses that investor sentiment plays a role in asset pricing. Behavioural finance takes into account the limits to arbitrage and states that asset prices may deviate from their fundamental values due to waves of irrational behaviour. This meaning that overly optimistic or pessimistic expectations can affect the markets for significant periods. (Schmeling 2009.)

Cryptocurrencies are often thought to miss intrinsic value, thus making them extremely hard to value. As a new asset class, the trading possibilities for cryptocurrency derivatives has been lacking in the history of cryptocurrencies as the derivatives market grows and expands as time passes. Thus, they are also hard to arbitrage. Baker and Wurgler (2007) state in their study that stocks which are hardest to value and most challenging to arbitrage are the most sensitive to sentiment. Based on the results on traditional financial assets, it is not far-fetched to suggest that investor sentiment has a significant role in the price formation and price fluctuation of cryptocurrencies as they have been classified to speculative financial assets by some.

The fluctuation of assets can be fully rational, based on fundamental changes. The fundaments may change due to earnings announcements, newly released information, macroeconomic changes, etc. There are many factors which may affect the fundamentals behind assets changing the demand that can be said to be rational reasons. However, some demand changes cannot be thought as rational. These changes can be better explained by irrational changes in investor sentiment or expectations. The traders that act on not rational reasons are described to be noise traders (Black 1986). If everyone trades on irrational reasons, we could not notice it in the prices as the trades cancel each other out. However, because of biases and heuristics that affect investors are studied to be the same, the trading between noise traders correlates, thus mowing the prices along with the irrational demand changes caused by noise traders. In addition, noise traders are not always driven away from the market by rational traders as their higher risk-taking may result in profits which attract others to follow their trading strategies. (Shleifer & Summers 1990.) Taking into account that cryptocurrencies have higher tails (Baur et al. 2018), it can be seen that irrational noise traders are rewarded more often due to higher risk-taking. Attracting more noise traders which derails the prices even further away from the potential fundamental value. Thus, it is essential to understand how sentiment affects cryptocurrencies as it may offer us more knowledge about the price formations.

4.1 Measures of investor sentiment

As there is not a single definition for investor sentiment, there is not a single measure for investor sentiment. Different measures may involve following a specific group of investors, using market proxies for investor sentiment, creating a composite index from market data or utilizing other statistics and data as proxies. The behavioural finance academic field has not reached a consensus on the best one, and in addition, the study research results differ between the same measures. (Klemola, Nikkinen & Peltomäki 2016.)

Direct measures of investor sentiment are often attained through polls and surveys which may be targeted to specific subgroups of market participants. An example of this is the American Association of Individual Investors (AAII) investor sentiment measure. The measure is received by conducting a poll in which AAII asks its members where they see the market being in the next six months, labelling answers as bullish, bearish and neutral. In contrast to the AAII survey, the Investors Intelligence (II) conducts its survey by gathering approximately 150 market newsletters and deduces each one of them as bullish, bearish or neutral. (Brown & Cliff 2004.) The former can be though to represent small investor sentiment as the latter can be thought to represent professional investors (Klemola et al. 2016).

In addition to the polls and surveys, consumer confidence is often used as a direct measure for investor sentiment. It can be seen that consumer confidence withholds the present and future expectations about the economy, which is often thought of as a synonym for the stock market by households. The two best-known consumer confidence measures are The University of Michigan's Consumer Confidence Index and the Conference Board Consumer Confidence Index. (Fisher & Statman 2003.) Compared to the other direct measures, it has one strong advantage. Consumer confidence is measured all around the developed countries in the same time interval, which offers possibilities for comparisons between countries. (Schmeling 2009.)

Investor sentiment proxy can be obtained from the market data; this kind of proxy is an indirect measurement proxy. This can be anything that can be seen to follow the sentiment of investors; most common proxies are VIX, put-call ratio, mutual fund data and discount of closed-end funds. (Klemola et al. 2016.) The use of these indirect measurements is based on the notion that some variables are thought to represent the market´s mood. However, some of these indirect measurements are related to direct measures. (Brown & Cliff 2004.)

As there is not a single measurement for investor sentiment, researchers have started to create composite sentiment indexes which combines multiple indirect sentiment measures, which captures the common trend by principal component analysis. Perhaps the most well-known is the Baker-Wurgler index which is built on the following measures: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. (Baker & Wurgler 2006.)

One of the newest trends is to use media attention, social media posts or search-engine results as a proxy for investor sentiment. Tetlock (2007) finds that media pessimism affects future stock returns and thus can be used as a proxy for investor sentiment. In a similar sense, Klemola et al. (2016) uses Google search volume index for positive or pessimistic search words and finds similar results as Tetlock (2007) as the results show that pessimistic search words are able to predict future negative returns. The use of google search-based sentiment measures can be seen more transparent as the market-derived measures as they are sums of various economic forces, and thus do not capture only the sentiment (Da, Engelberg & Gao 2015). In addition, Da et al. (2015) state that survey-based sentiment measures are beaten by search-based measures as the data is available on smaller time frames and the surveys may withhold dishonest answers as there are no incentives to answers honestly.

4.2 What drives sentiment

Investor sentiment can be seen to be driven by irrational beliefs or misinformation, but not all changes in investor sentiment are driven by irrational behaviour. The academic literature has concentrated much more on the topic can investor sentiment predict future stock returns than what causes changes in investor sentiment (Engelberg & Parsons 2013). To better understand how investor sentiment affects future stock returns, it is important to understand where changes to investor sentiment arise.

In their study, Engelberg and Parsons (2013) find that extreme market drops have an immediate effect on the hospitalization rate by psychological disorders. This is in agreement with the well-known prospect theory (Kahnemann & Tversky 1979) as the market surges do not decrease the hospitalization rates by psychological disorders, showing that people are risk-averse. They conclude that worries about the future affect the well-being of today. These findings are also noted in other literature as Fisher and Statman (2000), De Bondt (1993), and Brown and Cliff (2004) show that small and medium investors are affected by past stock earnings.

Investors can be affected by weather as well as it may affect the mood of an investor, which affect the decision making of the investor. This is shown by Hirshleifer and Shumway (2003) as their study find that returns are higher on sunny days than cloudy days. Their results show that psychological factors that affect decision making, for example, sunshine, may affect investor sentiment. The mood change can come from anywhere as Drakos (2010) shows that terrorist attacks cause lower returns on the day of the attack and the effect is amplified when the attack causes higher psychological impact to the population.

Media also has a role in the fluctuation of investor sentiment. Doms and Morin (2004) suggest that media affects investor sentiment through three channels: it indicates about the state of the economy via tone and volume of reporting, it may affect the probability that people change their opinion about the economy, and it reports about economic statistics and professional´s opinions. Further, the first channel may cause irrational behaviour to the markets via investor sentiment as media can drive the sentiment away independently, despite the background fundamentals and opinions of professional investors. When the volume of reporting increases while the tone is negative (reports about layoffs, a possible recession, etc.) it has a negative relationship to the investor sentiment. This is also shown to be the case when the reporting is higher than predicted by the fundamentals. This effect is more prominent during or after crises as the negative toned coverage has twice the effect on sentiment than during low volume news coverage.

These effects are reported to be efficient in the short-term periods and that the amount of coverage also affects to the fluctuation of investor sentiment. Similar results are found by Tetlock (2007) who finds that media pessimism is partly driven by past negative returns suggesting that negative returns may drive media to be irrationally pessimistic leading the sentiment further away from fundamentals.

4.3 Investor sentiment and cryptocurrencies

As cryptocurrencies are thought to be speculative assets (Baur et al. 2018; Baek & Elbeck 2015), it can be seen that they could act as extremely speculative stocks. Suggesting that investor sentiment could be one of the key drivers for cryptocurrencies fluctuation (Baker & Wurgler 2007; Corbet et al. 2019). As cryptocurrencies are not affected much by other financial assets (Corbet et al. 2019), the selection for investor sentiment proxy cannot be exactly copied from the existing literature about investor sentiment. As existing literature uses, for example, macro economical and financial data as an investor sentiment proxy. However, media, social media and search engines have been proven to act as investor sentiment proxy for stocks (Tetlock 2007; Klemola et al. 2016). From this, it can be thought that these platforms are suitable investor sentiment proxies for cryptocurrencies.

One of the first studies about investor sentiment was done by Kristoufek (2013), who studies the relationship between Bitcoins price and Google Trend data and Wikipedia searches using a dataset from 1st of May 2011 to 30th June 2013. The data for Google Trend data is weekly as for Wikipedia search queries the analysis is done on a daily basis. The analysis is done for Google Trend data using vector autoregression. As Bitcoin price data and Wikipedia search result data showed some evidence for cointegration, the analysis is done using a vector error correction model. The study results are in line with his assumptions that highly sceptical asset´s price is strongly affected by the investor sentiment. His results show that there is a very strong correlation between price and search engine interest. In addition, it is also shown that there is a causal relationship with the Google Trend data and Bitcoin prices; however, no evidence is found for a relationship with Wikipedia search results and Bitcoin prices. This might be due to different time intervals or differences between search engines. The shown relationship is also bidirectional, meaning that high fluctuation in Bitcoin´s price also affects more interest. This dynamic leads to a fluctuation that acts as the prices are high the increasing interest drives prices further and vice versa. These results suggest that the Bitcoin market is prone to potential bubbles. This also shown with formal statistical analysis as results also show that when the prices are above trend level, the increased interest pushes prices further, this is found for both search engine queries. Interestingly, it is shown with the Wikipedia data set that when the prices are below trend level, the interest drives the prices even deeper.

Eom et al. (2019) conduct an empirical study about the predictability and the statistical characteristics of Bitcoin return and volatility. Employing a time period of October 2013 – May 2017 using an autoregressive model to study if Google Trend index has capabilities to predict future prices or volatility in Bitcoin. In their study, they use Google trend index as a proxy for investor sentiment, the data being monthly. According to them, this is because investors often use google to find information about an asset, more searches meaning more interest. They find that investor sentiment has some abilities to explain future changes in Bitcoin volatility. Their findings suggest that investor sentiment affects Bitcoin significantly as it can explain future volatility changes in Bitcoin. Interestingly, they do not find any statistically meaningful explanatory powers in predicting Bitcoin by investor sentiment (cf. Kristoufek 2013). However, they note that their findings suggest that Bitcoin is comparable with speculative stocks, thus suggesting that investor sentiment has a significant role in Bitcoin´s price changes.

In a similar sense to Kristoufek (2013) and Eom et al. (2019), Nasir, Huynh, Nguyen and Duong (2019) study the effects of investor sentiment to the Bitcoin returns using Google Trend index as a proxy for investor sentiment and trading volume as a control variable. They employ vector autoregression, copulas approach and non-parametric drawings, to capture the relationship between sentiment and returns, using a weekly dataset from

2013 to 2017. Their vector autoregression and granger causality test results suggest that the relationship between sentiment and Bitcoin returns is unidirectional flowing from sentiment to the Bitcoin returns and lasts only for one period. In addition, their results show some evidence for that sentiment predicts trading volume for Bitcoin as well. The copulas and nonparametric methods agree with the more traditional methods.

Urquhart (2018) examines what causes investor attention in Bitcoin using vector autoregression and granger causality test. The study uses Google Trend index as a proxy for investor attention the time period for the study being 1st August 2010 – 31st July 2017. His results show that trading volume and volatility cause investor attention to Bitcoin the strongest predicting power belonging to one-day lag as well as returns with the strongest effect on a two-day lag. In contrast to Kristoufek (2013), Eom et al. (2019), and Nasir et al. (2019), he finds no evidence for predicting trading volume, volatility or returns by investor attention.

Subramaniam and Chakraborty (2020) take a different approach compared to the rest of the literature as they study the relationships of investor attention and cryptocurrency returns by quantile causality approach. Their dataset includes Bitcoin, Ethereum, Litecoin and Ripple, the time period for the study being January 2013 – March 2018, as some of the currencies did not trade for the whole period the time period varies between cryptocurrencies. As a proxy for investor sentiment, they use the Google Search Volume index the data being daily for returns and investor attention.

Their results for the causality in mean indicate that all of the cryptocurrencies have a bidirectional relationship with investor attention and returns. For Ethereum and Bitcoin, the returns granger causes investor attention in all quantiles as for Ripple this effect is only statistically significant during the poorest performance. The investor attention granger causes returns for Bitcoin and Ethereum similarly as for Bitcoin investor attention causes returns in extreme quantiles the sign is negative for the lowest quantile as for Ethereum the results are the same except for the middle quantile that causes positive returns. In contrast, for Ripple, investor attention causes return only during the superior performance. The results show that cryptocurrency markets experience attention-induced price pressure in higher quantiles. In addition, the study shows that the behaviour of cryptocurrencies differs between cryptocurrencies and market phases.

Bleher and Dimpfl (2019a) employ a bigger dataset and more frequencies for studying the predictive power of investor sentiment than most of the literature about investor sentiment and cryptocurrencies. They note that weekly frequency has dominated the literature as Google Search Volume index is available on longer time series only on a weekly frequency. However, using the finding of Bleher and Dimpfl (2019b), they are able to construct higher frequencies from Google Trends data by utilizing the concatenation method. They use 12 cryptocurrencies which are traded on Kraken.com in Euro with different time periods depending on the finding of the cryptocurrency, noting that the results of the study hold while using cryptocurrencies traded in US dollars. They construct individual sentiments for each cryptocurrency by using the most searched search term for corresponding cryptocurrencies. In addition, they use the search terms “cryptocurrency” and “Bitcoin” for measuring the market-wide interest to cryptocurrencies in addition to the individual sentiment proxies.

Bleher and Dimpfl (2019a) use vector autoregression models for the analysis by constructing five models which are compared to the base model 0, which is the simple univariate AR(p)-model. In order to prove that sentiment has predictive powers, the model must outperform the model 0 measured by the test developed by Clark and West (2006, 2007). The five models are following: first includes cryptocurrency specific sentiment proxy, second includes Google Search Volume index for the search term “Cryptocurrency”, third includes the Bitcoin sentiment proxy, fourth includes Google Search Volume indexes for cryptocurrency specific and “cryptocurrency”, as the Fifth includes cryptocurrency specific proxy, “cryptocurrency”, and “Bitcoin”. Their evidence for the returns are somewhat mixed as they find some predictive powers for Bitcoin, EOS-token and Litecoin, suggesting that it is not possible to explain future returns by

Google Search Volume index on a daily basis. Granger causality test shows that Google Search Volume index granger causes Ripple´s and EOSToken´s returns on a 5%-10% statistical significance level depending on the used model. For the weekly data, they use the same methodology for Bitcoin, Ethereum and Litecoin. The results show that model 5 for Ethereum and models 1,4 and 5 for Litecoin are able to explain future returns; however, they state that the effects are not significant enough on an economical level. On the hourly level, they conclude that the Google Search Volume index is not able to explain future returns. When considering all of their results, they conclude that the prediction power is negligible as for some cryptocurrencies the Google Search Volume index improves the prediction the forecast error is too big for economical significance. However, their results show for all of the cryptocurrencies that it is possible to predict volatility with Google Search Volume index, the prediction power being more prominent on lower frequencies (cf. Urquhart 2018).

Shen, Urquhart and Wang (2019) argue that Google Trend index is a poor proxy for well-informed investors as they are not going to google about cryptocurrencies; rather, they may be tweeting about cryptocurrencies. Thus, they state that Google Trend index is a measure for uninformed investor attention as the volume of tweets is a stronger proxy for investor attention. Studying the time period 4th September 2014 – 31st August 2018 using vector autoregression method Shen et al. (2019) studies can tweet volumes predict the daily fluctuation in Bitcoin returns, volatility and trading volume. They find a bidirectional relationship between the volume of tweets and trading volume and the volume of tweets and realized volatility. However, their results show only a little evidence for the ability to predict future returns. Thus, they conclude that there is no evidence for a relationship.

Kraaijeveld and Medt (2020) uses Twitter as a proxy for investor sentiment by performing a cryptocurrency specific lexicon-based sentiment analysis to the tweets analyzing nine different cryptocurrencies (Bitcoin, Ethereum, XRP, Bitcoin Cash, EOS, Litecoin, Cardano, Stellar and TRON) over the course 4th June 2018 and 4th August 2018 in daily frequency and hourly frequencies. The analyzed tweets are labelled as bullish, neutral or bearish, and from there, a sentiment proxy is constructed. They find that investor sentiment is able to predict daily returns as for hourly frequency, no causal relationships are found. For Ethereum investor sentiment has no predictive power; on the opposite, the sentiment indicator reacts to the market. As for Ripple investor sentiment is able to predict returns on the hourly level but not on a daily level. To summarize their results, it seems that investor sentiment constructed from tweets reacts more to the market than predicts the market. However, Kraaijeveld and Medt (2020) note that as their dataset is relatively small, the results might not represent the market comprehensively.

Guégan and Renault (2020) study the intraday effects of investor sentiment to Bitcoin prices using a time period of August 2017 – December 2019. They employ StockTwits messages as a proxy for investor sentiment and investor attention. StockTwits message board allow denoting a message as a bullish or bearish which allows to use it as a sentiment proxy. Using OLS regression and Granger causality tests they show that the StockTwits messages are able to predict future returns up to 15-minute intervals, the effect diminishing in more extended time periods, in contrast to the results of Kraaijeveld and Medt (2020). They also find that the past returns Granger causes the sentiment. Using the number of messages as a proxy for investor attention, they show that it does not have a statistically meaningful effect on the returns. However, their results are mainly driven by the results of the bubble period, when the effect of the sentiment was much more prominent than after the bubble period. Similar results were found by Rognone, Hyde and Zhang (2020) as they study how unscheduled news affect Bitcoin results in intra-day periods. Only positive news results in positive returns the effect being more substantial during bubble periods when even negative news leads to positive returns with a lag—showing some evidence that the market is more efficient after bubble periods.

Karalevicius, Degrande, Weerdt (2018) study Bitcoin´s value formation, focusing on sentiment´s effect on it rather than fundamental drivers. As a proxy for investor sentiment, they use Bitcoin expert media articles, websites that mainly cover Bitcoin. The sentiment index is created by analysing the articles by sentiment analysis. This meaning that the use of positive or negative words determine if it is positive or negative. By analysing the price patterns using investor sentiment as an explanatory variable, they are able to show that investor sentiment has some abilities to predict Bitcoin price movements in a semi-short-term time period. The pricing pattern following an overreaction towards the news sentiment. This is followed by a correction movement to another direction which is followed by traders that were late to move the price towards the sentiment until it incorporates all available information.

Gurdgiev and O'Loughlin (2020) study the effects of sentiment on ten cryptocurrencies using a robust variety of different sentiment indicators: VIX (proxies the fear in the market), US Equity market Uncertainty index (reflects the uncertainty in the financial markets), cryptocurrency sentiment (measures the sentiment towards cryptocurrencies), and CBOE Put/Call ratio (measures the bullishness/bearishness in the overall financial markets). As a cryptocurrency sentiment proxy, they use the posts by investors to the Bitcointalk.org forum about the studies' cryptocurrencies which are labelled bullish, neutral or bearish from where an index is created. The time period for the study being 1st January 2017 – 2nd April 2019 and the method being a generalized least squares panel model, as market-related indicators are available only on weekdays the study omits the weekend returns and absorbs them into weekday returns.

Gurdgiev and O'Loughlin (2020) find that uncertainty has a statistically significant positive effect to the cryptocurrency prices showing evidence that cryptocurrencies can be used as a hedge against uncertainty, similar results were found by Kristoufek (2015). Their cryptocurrency sentiment proxy also has a statistically significant positive relationship with returns which is shown to be stronger during the bear period of the market (19th December 2018 – 2nd April 2019), which shows evidence for herding behaviour in the cryptocurrency markets. The CBOE Put/Call ratio is statistically significant during the bear period of cryptocurrencies showing that the relationship is directional and conditional on bearish sentiment in the cryptocurrency markets. The fear factor, VIX index, is negatively statistically significant, showing evidence that cryptocurrencies do not offer a hedge possibility for fear in the financial markets.

5 Data and methodology

The purpose of this study is to study can investor attention predict cryptocurrency returns, to examine the interlinks of the cryptocurrency market, and to explain what causes attention to cryptocurrencies. For these purposes, data about cryptocurrency returns, Google Trends data and cryptocurrency trading volumes are utilized in three different statistical approaches.

5.1 Data

This study examines three different cryptocurrencies: Bitcoin, Ethereum and Ripple. The selection for cryptocurrencies is motivated by the market capitalization. As these three cryptocurrencies were the biggest cryptocurrencies by market capitalization in December 2019. This study uses the returns, Google Trends data and weekly trading volumes of the selected cryptocurrencies. The data for the returns and weekly trading volumes are obtained from (https://www.coinmarketcap.com). Coinmarketcap offers numerous statistics about cryptocurrencies and is widely used proxy for cryptocurrency prices as it is not exchange price biased towards one exchange as it combines prices from numerous exchanges (Kraaijeveld, and Smedt 2020). The proxy for investor attention is obtained from Google Trends. Google Trends measures the attention towards certain search words, and it is widely used proxy for investor attention and has been used in numerous cryptocurrency studies to proxy investor attention (Kristoufek 2013; Eom et al. 2019; Nasir et al. 2019; Urquhart 2018; Bleher & Dimpfl 2019a). The Google Trend data is constructed by normalizing the searches based on location and time. The data is scaled between 0-100 relatively to the popularity of all Google searches. This study employs the global Google trend data as Google Trends also offers a possibility for locational data. This study uses the search word “Bitcoin” for Bitcoin, “Ethereum” for Ethereum and “Ripple” for Ripple.

Due to Google Trend data´s weekly frequency, the analysis is conducted on a weekly frequency. The Google Trend data is updated on Sunday, and thus the weekly returns are calculated from the Sunday closing prices for cryptocurrencies. The weekly volumes are calculated by calculating the arithmetic average for the seven days, which is then used as a weekly measure for the trading volume proxying the trading activity during the week. The study is conducted on time period 1st January 2016 to 29th December 2019. This time period captures the pre-bubble phase of Bitcoin as well as almost two years of data after the bubble burst, offering relatively good sample as it is heterogeneous. The selection of the time period is motivated by data availability as earlier time periods do not provide Google Trend data points for all of the selected cryptocurrencies as if there is not enough Google Searches for a search word the recorded value for the Trends index is zero.

Figure 1. Bitcoin price development in US dollars

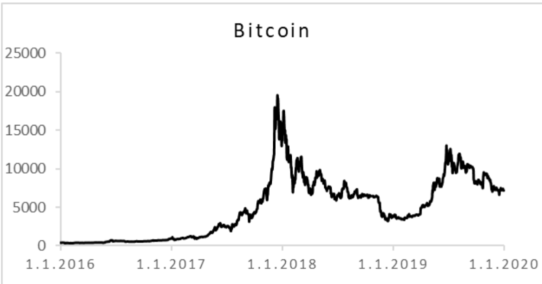


Figure 2. Ethereum price development in US dollars

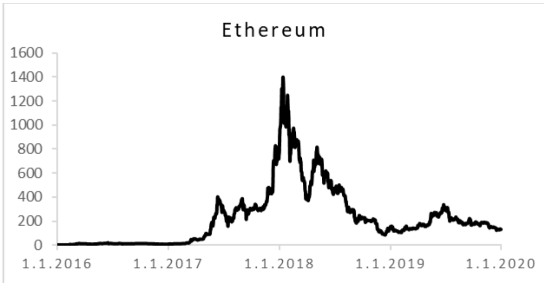
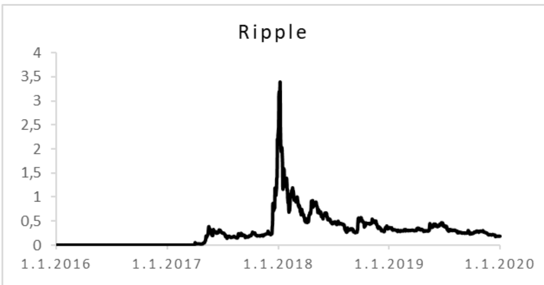


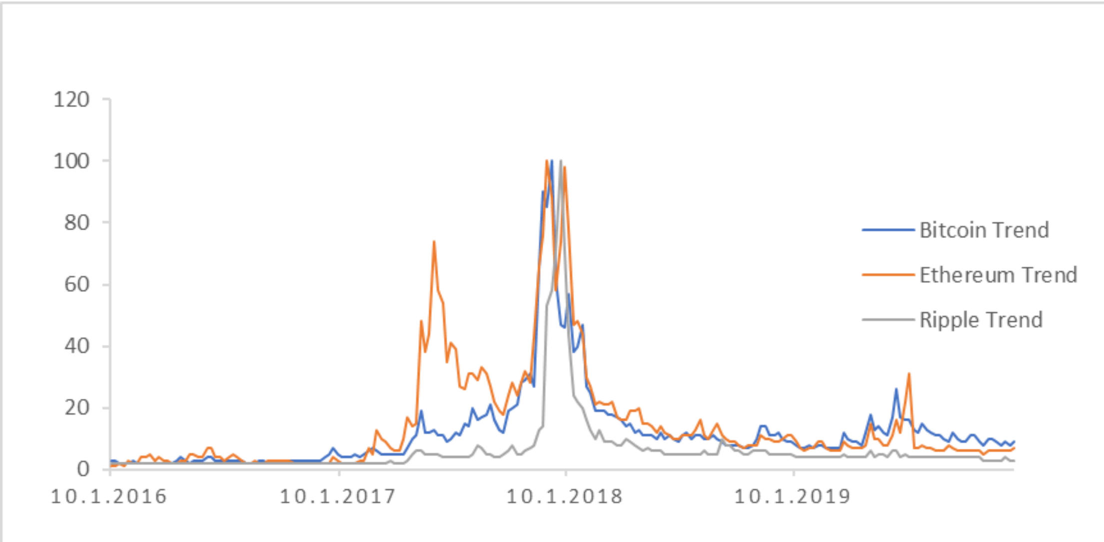
Figure 3. Ripple price development in US dollars



From figures 1-3, it is easy to interpret that the price series are correlated, and in the big picture, prices move align. The first one and half years of the time period the prices were relatively low compared to the prices of the bubble stage. However, the pre-bubble phase is interesting for Ripple as for Bitcoin and Ethereum the prices trend upwards for the whole 2017 as for Ripple the price surges at the end of 2017. It is also noticeable that Bitcoin seems to lead Ripple and Ethereum as its price movements occur a little bit before compared to Ripple´s and Ethereum´s prices for most parts. After the bubble phase, the prices are more stable, and there does not occur as much volatility which is evident especially for Ripple.

From figure 4, we observe that for the most parts, investor attention is correlated with the prices. The investor attention surges during the bubble phase and similar movements can be seen for the whole time period. Except for the mid-2017 surge in investor attention to Ethereum the trends comove for the whole period. Interestingly it seems that Ripple´s investor attention lags Bitcoin and Ethereum, which may signal that it follows the two bigger cryptocurrencies in returns and investor attention.

Figure 4. Google trends data for Bitcoin, Ethereum and Ripple



To assure that the variables are stationary the weekly returns and trading volumes are calculated by natural logarithm changes and Google Trends data is first differenced. The descriptive statistics are presented in table 1. From the three cryptocurrencies, Ethereum has the highest mean weekly return of 2,4% as the mean returns for Bitcoin and Ripple are 1,4% and 1,7%. The selected cryptocurrencies behave as stocks when taking into account market capitalization as the smaller not so mature Ripple is the most volatile of them all Bitcoin being least volatile. Bitcoin is negatively skewed as earlier literature has shown (Baur et al. 2018) as Ripple and Ethereum are positively skewed which is in line with the rest of the results as Ethereum and Ripple experience few extreme gains during the time period and also have higher maximum weekly returns. The return time series for Bitcoin behaves the best when considering normality as Ethereum is moderately skewed and exhibit kurtosis as Ripple is highly skewed and exhibit high kurtosis. This can also be noticed from the Jarque-Bera test; it is safe to say that not any of the variables behave like a normal distribution.

Similar observations can be made from the Google Trend data first differences. Ripple´s trend data is highly kurtosis and has the lowest standard deviation as the lowest mean first difference. This means that Ripple´s investor attention does not fluctuate a lot during the time period but has some very big positive surges. As in price data, the behaviour for Bitcoin and Ethereum is much more similar to each other compared to the Ripple. For all of the investor attention proxies the median and mean change is close to zero, meaning that during most of the weeks, the investor attention proxy does not fluctuate. For the trading volume changes, the findings are similar to the prices and investor attention as Bitcoins trading volume behaves the best of the three and is the least volatile of them. Interestingly Ethereum´s trading volume behaviour is closer to Ripple than to Bitcoin. The stationarity of the time series is tested by using the Augmented Dickey-fuller test, shown in table 1., in which we are able to reject the null hypothesis for unit root, meaning that all of our time series are stationary.

Table 2 reports the correlation matrix for the selected variables in which the Google trend and Trading volume time series are lagged by one week to the returns to show some potential prediction power. As earlier noted in the cryptocurrency literature, the cryptocurrencies are interlinked to each other, which is shown in the correlation between cryptocurrency returns (Corbet et al. 2018; Ji et al. 2019). Further, Ferreira and

Pereira (2019) suggest that the cryptocurrency market became even more interlinked after the pricing bubble of cryptocurrencies. The results are somewhat mixed for the investor attention proxies as Bitcoin does not show any correlation to its own returns but shows a negative relationship with the return of Ethereum and Ripple. This suggests that as the investor attention to Bitcoin increases the future returns of Ethereum and Ripple are negative. For Ethereum´s investor attention, there is a weak positive correlation to the prices of Bitcoin and Ethereum and extremely weak negative correlation to Ripple´s returns. Surprisingly, Ripple´s investor attention has the highest correlation to the future returns of all of the cryptocurrencies showing modest positive correlation to its own returns. The investor attention proxies of Bitcoin and Ethereum show some modest positive correlation suggesting that they might behave similarly.

In contrast, Bitcoin´s and Ripple´s investor attentions are slightly negatively correlated. This meaning that when the investor attention of Bitcoin falls the investor attention of Ripple grows and vice versa. This can be seen in figure 4 as Ripple´s investor attention follows the investor attention of Bitcoin with a lag. This may signal that the investor attention spillovers in the market with a lag from larger cryptocurrencies to smaller cryptocurrencies. Similar results were found by Bitcoin´s investor attention and Ripple´s returns showing that there are differences between relationships in the cryptocurrency market. Ripple´s investor attention is weakly positively correlated to the Ethereum´s investor attention. The trading volumes do not seem to have any predictive power to the returns and are not correlated to the investor attention proxies. Though, the trading volumes are somewhat correlated, especially Bitcoin and Ethereum, which indicates that trading volumes move together in the cryptocurrency market.

Table 1. Descriptive statistics of variables

	Bitcoin ΔPrice	Ethereum ΔPrice	Ripple ΔPrice	Bitcoin ΔTrend	Ethereum ΔTrend	Ripple ΔTrend	Bitcoin ΔVolume	Ethereum ΔVolume	Ripple ΔVolume
Mean	0,014	0,024	0,017	0,029	0,029	0,005	0,030	0,048	0,040
Median	0,016	0,013	-0,005	0,000	0,000	0,000	0,008	-0,002	-0,011
Maximum	0,347	0,646	1,857	38	33	39	0,773	1,673	2,203
Minimum	-0,353	-0,431	-0,597	-38	-31	-29	-0,700	-0,994	-1,688
Std. Dev.	0,112	0,179	0,238	5,323	6,759	4,796	0,256	0,434	0,588
Skewness	-0,222	0,588	3,165	0,096	0,261	1,498	0,390	0,929	0,803
Kurtosis	4,045	4,577	23,209	30,392	13,119	41,020	3,389	5,566	5,410
Jarque-Bera	11,109	33,352	3868,096	6471,645	885,578	12544,910	6,538	86,560	72,348
Probability	0,004	0,000	0,000	0,000	0,000	0,000	0,038	0,000	0,000
ADF	-13,816	-12,732	-12,991	-13,965	-7,831	-8,531	-15,296	-16,957	-16,726
Probability	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Sum	2,808	4,904	3,499	6,000	6,000	1,000	6,226	10,026	8,243
Sum Sq. Dev.	2,595	6,617	11,672	5837,826	9411,826	4738,995	13,519	38,751	71,126
Observations	207	207	207	207	207	207	207	207	207

Table 2. Correlations between variables. Trend and volume being lagged by one week

	Bitcoin ΔPrice	Ethereum ΔPrice	Ripple ΔPrice	Bitcoin ΔTrend	Ethereum ΔTrend	Ripple ΔTrend	Bitcoin ΔVolume	Ethereum ΔVolume	Ripple ΔVolume
Bitcoin ΔPrice	1,00	0,49	0,41	0,02	0,08	0,22	0,07	-0,04	0,03
Ethereum ΔPrice	0,49	1,00	0,44	-0,13	0,17	0,20	0,17	0,09	0,10
Ripple ΔPrice	0,41	0,44	1,00	-0,18	-0,05	0,43	0,10	0,05	0,19
Bitcoin ΔTrend	0,02	-0,13	-0,18	1,00	0,43	-0,11	0,01	0,07	0,02
Ethereum ΔTrend	0,08	0,17	-0,05	0,43	1,00	0,26	0,07	0,00	0,02
Ripple ΔTrend	0,22	0,20	0,43	-0,11	0,26	1,00	0,07	-0,04	0,04
Bitcoin ΔVolume	0,07	0,17	0,10	0,01	0,07	0,07	1,00	0,58	0,30
Ethereum ΔVolume	-0,04	0,09	0,05	0,07	0,00	-0,04	0,58	1,00	0,28
Ripple ΔVolume	0,03	0,10	0,19	0,02	0,02	0,04	0,30	0,28	1,00

5.2 Methodology

In this thesis, the relationship between investor sentiment and cryptocurrencies is examined by using the same methods as Klemola et al. (2016.). The exception being that Klemola et al. (2016) use investor sentiment as proxy counting for bullish and bearish sentiment as this study uses investor attention as a proxy for investor sentiment not separating between bullish and bearish sentiment. A similar approach has also been previously conducted for Bitcoin using investor attention as a main explanatory variable and trading volume as a control variable by Nasir et al. (2019). The study is done by using the following methods: OLS-regression, Vector auto-regression and Granger causality test.

The possible impact of investor sentiment on cryptocurrency returns is evaluated with the following OLS-Regression:

$$\Delta Currency_t = \beta_0 + \beta_1(\Delta Index_{t-1}) + \beta_2(\Delta Volume_{t-1}) + \epsilon_t \tag{2}$$

where the dependent variable $\Delta Currency_t$ is the weekly natural logarithmic change for Sunday closing price of the analysed cryptocurrency. The main interest of the analysis lies in the independent variable $\Delta Index_{t-1}$ which is the weekly first difference for the used investor sentiment proxy with a lag of one week. As the second independent variable $\Delta Volume_{t-1}$ is the weekly logarithmic change for week´s average daily volume of the analysed cryptocurrency with a lag of one week, used as a control variable. The OLS-regression is completed nine times as the returns of all of the three cryptocurrencies are regressed on to the three investor sentiment proxies of cryptocurrencies keeping the trading volume variable as same for all of the three OLS-regressions for each particular cryptocurrency. To ensure the robustness of the results and the underlying autocorrelation and heteroskedasticity in financial data, the standard errors are corrected for heteroskedasticity and autocorrelation by the Newey-West method.

As the variables were stationary, we are able to use the vector autoregression model. Which is evaluated by the following models:

$$\Delta Currency_t = \beta_0 + \sum_{s=1}^{4} \beta_1(\Delta Currency_{t-s}) + \sum_{i=1}^{4} \beta_2(\Delta Index_{t-i}) + \sum_{v=1}^{4} \beta_3(\Delta Volume_{t-v}) + \epsilon_t \tag{3}$$

$$\Delta Index_t = \beta_0 + \sum_{s=1}^{4} \beta_1(\Delta Currency_{t-s}) + \sum_{i=1}^{4} \beta_2(\Delta Index_{t-i}) + \sum_{v=1}^{4} \beta_3(\Delta Volume_{t-v}) + \epsilon_t \tag{4}$$

$$\Delta Volume_t = \beta_0 + \sum_{s=1}^{4} \beta_1(\Delta Currency_{t-s}) + \sum_{i=1}^{4} \beta_2(\Delta Index_{t-i}) + \sum_{v=1}^{4} \beta_3(\Delta Volume_{t-v}) + \epsilon_t \tag{5}$$

where $\Delta Currency_{t-s}$ is the weekly logarithmic change for Sunday opening of the analysed cryptocurrency with different weekly lags, $\Delta Index_{t-i}$ which is the weekly first difference for the used investor sentiment proxy with different weekly lags, $\Delta Volume_{t-v}$ is the weekly logarithmic change for week´s average daily volume of the analysed cryptocurrency with different weekly lags. Similarly, to the OLS-regression, this is performed nine times by using all of the investor attention measures for all of the returns of the three cryptocurrencies resulting.

Appendix 1 presents the used lag-length criteria for the vector autoregression models. As we employ nine separate vector autoregression models, we have nine different lag-length criteria for the individual models. To make the results more uniform, we employ one single lag-length for all of the models despite the individual suggestions. The results for the lag-length criteria are noisy as the suggested lag-lengths vary between zero and eight for the analysed vector autoregression models. Schwarz information criterion and Hannan-Quinn information criterion suggest lag-lengths of 0-3 as the sequential modified LR test statistic, final prediction error and Akaike information criterion suggest lag-lengths between one and eight. The selected lag-length of 4 is a compromise between the criteria and also offers lags for a whole month.

In addition, this study uses the Granger causality test to test further the relationship between investor attention and cryptocurrency returns to capture if the relationship is one-directional or bidirectional. The Granger causality test analyses if investor attention has some information which helps to forecast future cryptocurrency returns. Further, the test is also conducted to see if cryptocurrency returns have some information which helps to forecast future investor attention to the cryptocurrencies.

Finally, this study uses different time periods and one single multiple OLS-regression model for all of the cryptocurrencies to test the robustness of the results. This is conducted by dividing the time period into two sub-samples. Literature shows that the cryptocurrencies´ market dynamic changes over time and the market became more efficient after 2017 (Tran & Leivik 2019; Urquhart 2016; Kyriazis 2019). Thus, the time period is divided into two sub-samples: 1st of January 2016 – 8th of April 2018 and 9th of April 2018 - 29th December 2019. This provides two different market environments to analyse as the first period withholds the bubble forming and sell-off periods as the latter time period represents a more stable market environment. The multiple OLS-regression models withhold all of the three investor attention proxies for the three cryptocurrencies, and the OLS-regression is conducted separately for all of the three cryptocurrencies. This might add some more information about the interlinked nature of the cryptocurrency market as one investor attention proxy might be dominated by others. The estimated multiple OLS-regression models are:

$$\Delta Currency_t = \beta_0 + \sum_{i=1}^{3} \beta_1 \left(\Delta Index_{t-1,i}\right) + \beta_2 (\Delta Volume_{t-1}) + \epsilon_t \tag{6}$$

where the dependent variable $\Delta Currency_t$ is the weekly natural logarithmic change for Sunday closing price of the analysed cryptocurrency. $\Delta Index_{t-1,i}$ is the weekly first difference for the three investor attention proxies with a lag of one week. As the second independent variable $\Delta Volume_{t-1}$ is the weekly logarithmic change for week´s average daily volume of the analysed cryptocurrency with a lag of one week. Table 2 presents the correlation matrix, which shows that there is no concern for multicollinearity as all of the independent variables used in the multiple OLS-regression models remain within acceptable limits (< 0,7).

6 Empirical analysis

The results of the empirical analysis are presented in the following section. Firstly, the OLS-regression results are presented, as in the following section, the Vector autoregression and Granger causality test results are discussed. The section is ended by robustness tests to the OLS-regression results.

6.1 OLS regression results

The results for the equation (2) are presented in table 3, where ΔPrice is the corresponding return for the analysed cryptocurrency, ΔTrend is the corresponding first differenced investor attention proxy to the cryptocurrency with a lag of one week, and ΔVolume is the weekly natural logarithmic change for a week´s average daily trading volume of the corresponding cryptocurrency with a lag of one week.

The OLS regression results show that the near-term return of Bitcoin cannot be predicted by the investor sentiment of Bitcoin and Ethereum. However, the investor sentiment for Ripple has a statistically significant positive effect. The control variable is insignificant for all of the three regressions. Coefficients are also supported by the adjusted R^2 as the regression with the lagged trend of Ripple has the highest (4,1%) as the adjusted R^2´s are practically zero for the other two regressions. These results are in line with Urquhart (2018), and Bleher and Dimpfl (2019a) as the investor attention of Bitcoin is found to have no predictive power to the returns of Bitcoin. Surprisingly, Ripple´s investor attention has a highly statistically significant positive effect to the next week returns of Bitcoin. Earlier literature has shown that Bitcoin´s returns are a driver for Ripple´s returns the relationship being unidirectional. However, it seems that the investor attention of Ripple is a driver for Bitcoin´s returns (Corbet et al. 2018). This may suggest that investor attention to smaller cryptocurrencies has a spillover effect on the larger cryptocurrencies returns.

Table 3. OLS-regression estimates

Dependent variable:	Bitcoin ΔPrice				Ethereum ΔPrice				Ripple ΔPrice		
C	0,013*			C	0,021			C	0,015		
	(1,729)				(-1,454)				(-1,130)		
Bitcoin ΔTrend	0,0005			Ethereum ΔTrend	0,005***			Ripple ΔTrend	0,021***		
	(0,202)				(2,923)				(4,630)		
Bitcoin ΔVolume	0,03226			Ethereum ΔVolume	0,036			Ripple ΔVolume	0,069***		
	(0,901)				(1,270)				(2,685)		
C		0,014*		C		0,021		C		0,014	
		(1,762)				(-1,364)				(0,894)	
Ethereum ΔTrend		0,00123		Bitcoin ΔTrend		-0,005***		Ethereum ΔTrend		-0,002	
		(0,761)				(-2,866)				(-0,637)	
Bitcoin ΔVolume		0,02999		Ethereum ΔVolume		0,041		Ripple ΔVolume		0,076***	
		(0,854)				(1,467)				(2,816)	
C			0,014*	C			0,020	C			0,015
			(1,839)				(1,431)				(0,882)
Ripple ΔTrend			0,005***	Ripple ΔTrend			0,007***	Bitcoin ΔTrend			-0,008**
			(8,202)				(3,308)				(-2,092)
Bitcoin ΔVolume			0,02567	Ethereum ΔVolume			0,040	Ripple ΔVolume			0,077***
			(0,780)				(1,435)				(2,764)
Adjusted R^2	-0,004	0,001	0,041	Adjusted R^2	0,028	0,018	0,038	Adjusted R^2	0,203	0,028	0,059
Prob(F-statistic)	0,540	0,325	0,005	Prob(F-statistic)	0,022	0,060	0,007	Prob(F-statistic)	0,000	0,020	0,001
Durbin-Watson	2,005	2,038	2,015	Durbin-Watson	1,951	1,829	1,910	Durbin-Watson	2,180	2,000	1,946

Table 3 reports the OLS-regression estimates where the coefficient is reported next to the variable and the t-stat for the coefficient is located under the coefficient in parenthesis.

*** Statistical significance at the 1% level

** Statistical significance at the 5% level

* Statistical significance at the 10% level

The results for Ethereum differ from Bitcoin´s results as all of our investor sentiment proxies have statistically significant relationships with the next week return, the results for the control variable do not differ from Bitcoin results. Interestingly, the relationship is positive for the investor attention proxies of Ethereum and Ripple but negative for Bitcoin´s. The adjusted R^2´s are similar as Ripple´s investor sentiment explains the most (3,8%), Ethereum´s second most (2,8%) and Bitcoin´s the least (1,8%). These results showing that Ripple´s Investor attention has the most power to explain the next week returns of Ethereum.

The regression results for Ripple are not in line with the other two cryptocurrencies. Our control variable is significant for all of the three regressions. In addition, as its own investor attention has a statistically significant positive relationship the investor attentions of Bitcoin and Ethereum have a negative relationship, Bitcoin´s being statistically significant. From all of the nine regressions the highest adjusted R^2 is for the regression that regresses Ripple´s own attention and volume to its price change, explaining 20% of the price changes. While using Bitcoin´s investor sentiment proxy, we are able to explain 6% of the Ripple price changes when for Ethereum investor sentiment the adjusted R^2 is 2,8%.

The regression results have significant differences for all of the cryptocurrencies signalling that the behaviour of these three currencies differ from each other. The results agree with the correlation matrix as the cryptocurrencies behave differently, and Ripple´s investor attention has the best ability to predict next week returns. Bitcoin seems to be the most efficient as there is only one statistically significant coefficient and the adjusted coefficient of determinations are close to zero for all three regressions. Its investor attention proxy has a statistically significant negative effect to the next week returns of Ethereum and Ripple, suggesting that increased attention to Bitcoin predicts negative returns in the next week.

All of the investor attention proxies can predict the price changes of Ethereum, the relationship being positive for its own investor attention proxy and Ripple´s investor attention proxy. However, the relationship turns negative for Bitcoin´s investor sentiment signalling that rise in the investor attention of Bitcoin predicts negative returns in the next week for Ethereum. In addition, the investor attention proxy for Ethereum has no abilities for predicting future returns in Bitcoin and Ripple. These results are somewhat in line with earlier literature as Ethereum has been founded to be dominated by the price development of bigger and smaller cryptocurrencies, acting as a recipient not a sender of price shocks (Ji et al. 2019).

The results for Ripple suggest that its behaviour is not as efficient as Ethereum and Bitcoin. Ripple´s next week returns can be predicted by its own trading volume suggesting that it experiences herding as high trading volume weeks lead to higher returns in the next week which is in line with the findings of Kallinterakis and Wang (2019). It is also heavily affected by its own investor attention, and the OLS-regression results are most robust to its own investor attention and trading volume. Ripple´s investor attention seems to be the most significant predictor of next week returns which agrees with the results of Kallinterakis and Wang (2019) as they document that herding arises from the smaller cryptocurrencies herding towards larger cryptocurrencies.

6.2 Vector autoregression and granger causality test results

The results for the equations (3) - (5) are presented in tables 4-6 where ΔPrice is the corresponding return for the analysed cryptocurrency whit lags up to four, ΔTrend is the corresponding first differenced investor attention proxy to the cryptocurrency with lags up to four, and ΔVolume is the weekly natural logarithmic change for a week´s average daily trading volume of the corresponding cryptocurrency with lags up to four.

The vector autoregression results show that investor attention has a predictive power to the near-term returns. For Bitcoin, the effect seems to be more lagged as it´s investor sentiment with two lags seems to predict statistically significant returns. When the investor attentions of Ethereum and Ripple predict statistically significant positive returns with a one-week lag. However, the results for the two-week lag of Bitcoin attention and Ethereum one-week lag are somewhat negligible taking into account the adjusted R^2. Thus, the results align with the OLS-regression results. In addition, Bitcoin´s trading volume can be predicted by its price and investor attention as both have a statistically positive relationship with the trading volume.

Table 4. Vector autoregression estimates for Bitcoin

Variable	Bitcoin ΔPrice	t-stat	Bitcoin ΔTrend	t-stat	Bitcoin ΔVolume	t-stat
Bitcoin ΔPrice(-1)	0,025	0,321	14,603	4,085	0,456	2,953
Bitcoin ΔPrice(-2)	-0,004	-0,045	-6,562	-1,723	0,257	1,560
Bitcoin ΔPrice(-3)	0,043	0,521	-4,856	-1,282	0,557	3,404
Bitcoin ΔPrice(-4)	-0,143	-1,714	8,142	2,141	-0,276	-1,680
Bitcoin ΔTrend(-1)	0,000	0,147	-0,015	-0,198	0,016	5,079
Bitcoin ΔTrend(-2)	0,004	2,388	0,085	1,089	-0,004	-1,112
Bitcoin ΔTrend(-3)	0,002	0,901	-0,098	-1,249	0,004	1,259
Bitcoin ΔTrend(-4)	-0,001	-0,331	-0,200	-2,655	0,003	0,925
Bitcoin ΔVolume(-1)	-0,002	-0,047	-1,456	-0,832	-0,142	-1,880
Bitcoin ΔVolume(-2)	0,003	0,079	1,066	0,621	-0,229	-3,091
Bitcoin ΔVolume(-3)	-0,013	-0,351	1,275	0,736	-0,090	-1,203
Bitcoin ΔVolume(-4)	0,017	0,532	0,093	0,062	0,042	0,651
C	0,015	1,876	-0,145	-0,390	0,027	1,650
Adjusted R^2	0,023		0,108		0,237	
F-statistic	1,390		3,035		6,225	
AIC	-1,494		6,149		-0,135	
SIC	-1,282		6,361		0,077	

Variable	Bitcoin ΔPrice	t-stat	Ethereum ΔTrend	t-stat	Bitcoin ΔVolume	t-stat
Bitcoin ΔPrice(-1)	-0,030	-0,380	5,744	1,275	0,432	2,767
Bitcoin ΔPrice(-2)	0,006	0,074	2,420	0,526	0,398	2,497
Bitcoin ΔPrice(-3)	0,073	0,889	6,536	1,406	0,443	2,750
Bitcoin ΔPrice(-4)	-0,193	-2,358	-8,209	-1,765	-0,346	-2,145
Ethereum ΔTrend(-1)	0,003	2,007	0,014	0,180	0,013	5,032
Ethereum ΔTrend(-2)	0,000	0,066	-0,385	-4,792	0,000	0,107
Ethereum ΔTrend(-3)	0,002	1,580	0,101	1,276	0,001	0,316
Ethereum ΔTrend(-4)	0,000	0,038	0,014	0,172	0,000	0,075
Bitcoin ΔVolume(-1)	0,028	0,742	3,368	1,576	-0,201	-2,716
Bitcoin ΔVolume(-2)	-0,005	-0,143	3,741	1,743	-0,208	-2,795
Bitcoin ΔVolume(-3)	-0,028	-0,747	0,287	0,134	-0,110	-1,489
Bitcoin ΔVolume(-4)	0,017	0,506	4,641	2,431	0,051	0,775
C	0,016	1,931	-0,430	-0,914	0,029	1,787
Adjusted R^2	0,012		0,137		0,234	
F-statistic	1,201		3,682		6,142	
AIC	-1,483		6,593		-0,132	
SIC	-1,271		6,805		0,080	

Variable	Bitcoin ΔPrice	t-stat	Ripple ΔTrend	t-stat	Bitcoin ΔVolume	t-stat
Bitcoin ΔPrice(-1)	-0,001	-0,018	-0,501	-0,174	0,649	4,140
Bitcoin ΔPrice(-2)	0,025	0,323	8,603	2,868	0,478	2,920
Bitcoin ΔPrice(-3)	0,026	0,320	10,067	3,212	0,362	2,119
Bitcoin ΔPrice(-4)	-0,231	-2,880	-5,254	-1,684	-0,359	-2,107
Ripple ΔTrend(-1)	0,006	3,531	0,237	3,483	0,006	1,639
Ripple ΔTrend(-2)	-0,001	-0,633	0,015	0,220	0,004	1,048
Ripple ΔTrend(-3)	0,001	0,310	0,033	0,484	-0,002	-0,632
Ripple ΔTrend(-4)	0,001	0,836	-0,321	-4,822	0,002	0,490
Bitcoin ΔVolume(-1)	0,030	0,844	1,197	0,879	-0,212	-2,849
Bitcoin ΔVolume(-2)	0,003	0,090	-0,967	-0,701	-0,222	-2,951
Bitcoin ΔVolume(-3)	-0,009	-0,261	1,406	1,022	-0,064	-0,859
Bitcoin ΔVolume(-4)	0,014	0,437	1,187	0,937	0,057	0,819
C	0,016	1,988	-0,267	-0,853	0,026	1,517
Adjusted R^2	0,052		0,227		0,144	
F-statistic	1,928		5,936		3,825	
AIC	-1,525		5,798		-0,020	
SIC	-1,313		6,010		0,192	

The vector autoregression supports the OLS regression results of Ethereum´s price changes as the investor attention proxies are statistically significant only at the first lag having the same signs as the OLS regression results, the relationship being relatively weak with the investor attention of Bitcoin. As for Bitcoin, Ripple´s investor attention proxy seems to have the most predictive power for near-term future returns. Similar results for the trading volume are found as for Bitcoin, as the trading volume can be predicted by the first two lags of returns and by the first lag of its own investor attention proxy.

However, the results for Ripple tells us more information about the relationship with its price and our investor sentiment proxies. The results for the first lags agree with our OLS regression results, showing that its own investor sentiment has extremely significant predictive power for the next week returns. Surprisingly, our investor attention proxies of Bitcoin and Ethereum experience a sign change after the first lag. Bitcoin´s investor sentiment has a statistically significant positive relationship with price changes of Ripple during lags two and three as Ethereum´s investor sentiment has a statistically significant positive relationship with lags of three and four. These results imply that Ripple´s price is influenced by Bitcoin´s and Ethereum´s investor sentiments, but the effect is more lagged than for the other two cryptocurrencies. This can be interpreted that as the interest grows towards our bigger cryptocurrencies, it has a spill-over effect on the price of Ripple, which transmits in two to four weeks. Ripple´s trading volume has a similar relationship with its own investor attention, and returns as Bitcoin and Ethereum as the first lag of both variables have a statistically significant positive effect on the trading volume.

Table 5. Vector autoregression estimates for Ethereum

Variable	Ethereum ΔPrice	t-stat	Ethereum Δtrend	t-stat	Ethereum ΔVolume	t-stat
Ethereum ΔPrice(-1)	0,004	0,051	2,381	0,806	0,368	2,177
Ethereum ΔPrice(-2)	0,084	1,051	2,881	0,983	0,409	2,445
Ethereum ΔPrice(-3)	0,119	1,503	3,910	1,339	0,091	0,547
Ethereum ΔPrice(-4)	-0,156	-1,995	-10,007	-3,483	-0,185	-1,124
Ethereum Δtrend(-1)	0,005	2,689	0,073	1,017	0,026	6,404
Ethereum Δtrend(-2)	-0,001	-0,332	-0,291	-3,722	0,000	0,045
Ethereum Δtrend(-3)	0,002	1,137	0,162	2,098	0,006	1,440
Ethereum Δtrend(-4)	0,001	0,315	0,026	0,330	0,003	0,671
Ethereum ΔVolume(-1)	0,025	0,667	0,357	0,259	-0,322	-4,085
Ethereum ΔVolume(-2)	0,028	0,718	0,386	0,272	-0,225	-2,771
Ethereum ΔVolume(-3)	0,039	1,015	0,737	0,521	-0,110	-1,356
Ethereum ΔVolume(-4)	0,032	0,976	-0,216	-0,178	-0,028	-0,399
C	0,013	1,031	0,023	0,049	0,049	1,872
Adjusted R^2	0,056		0,144		0,247	
F-statistic	1,998		3,830		6,536	
AIC	-0,628		6,585		0,861	
SIC	-0,416		6,797		1,073	

Variable	Ethereum ΔPrice	t-stat	Bitcoin Δtrend	t-stat	Ethereum ΔVolume	t-stat
Ethereum ΔPrice(-1)	0,080	0,982	2,376	0,933	0,576	3,098
Ethereum ΔPrice(-2)	0,107	1,320	-2,204	-0,866	0,477	2,567
Ethereum ΔPrice(-3)	0,126	1,557	0,553	0,216	0,164	0,879
Ethereum ΔPrice(-4)	-0,132	-1,708	-0,984	-0,405	-0,100	-0,562
Bitcoin Δtrend(-1)	-0,004	-1,891	0,030	0,408	0,010	1,804
Bitcoin Δtrend(-2)	0,002	0,966	0,013	0,177	0,002	0,401
Bitcoin Δtrend(-3)	0,003	1,355	-0,016	-0,208	0,007	1,321
Bitcoin Δtrend(-4)	0,002	0,890	-0,166	-2,216	0,005	0,856
Ethereum ΔVolume(-1)	0,000	-0,006	-1,017	-0,922	-0,389	-4,828
Ethereum ΔVolume(-2)	0,013	0,357	0,069	0,060	-0,258	-3,041
Ethereum ΔVolume(-3)	0,037	1,004	1,193	1,031	-0,094	-1,117
Ethereum ΔVolume(-4)	0,032	0,967	-0,145	-0,141	-0,030	-0,398
C	0,012	0,944	0,040	0,103	0,043	1,512
Adjusted R^2	0,052		-0,008		0,103	
F-statistic	1,931		0,865		2,925	
AIC	-0,624		6,272		1,037	
SIC	-0,412		6,484		1,249	

Variable	Ethereum ΔPrice	t-stat	Ripple ΔTrend	t-stat	Ethereum ΔVolume	t-stat
Ethereum ΔPrice(-1)	0,038	0,489	-2,605	-1,258	0,604	3,321
Ethereum ΔPrice(-2)	0,101	1,280	3,248	1,555	0,486	2,652
Ethereum ΔPrice(-3)	0,118	1,489	-1,998	-0,957	0,092	0,501
Ethereum ΔPrice(-4)	-0,127	-1,639	-1,723	-0,845	-0,071	-0,397
Ripple ΔTrend(-1)	0,005	2,080	0,268	3,891	0,010	1,704
Ripple ΔTrend(-2)	0,004	1,487	0,033	0,461	0,007	1,097
Ripple ΔTrend(-3)	-0,002	-0,553	0,085	1,180	-0,004	-0,666
Ripple ΔTrend(-4)	0,003	1,304	-0,314	-4,518	0,005	0,870
Ethereum ΔVolume(-1)	0,008	0,241	0,666	0,740	-0,376	-4,760
Ethereum ΔVolume(-2)	0,028	0,784	1,204	1,270	-0,246	-2,954
Ethereum ΔVolume(-3)	0,037	1,042	0,751	0,797	-0,091	-1,099
Ethereum ΔVolume(-4)	0,029	0,891	0,728	0,850	-0,026	-0,350
C	0,012	0,977	-0,055	-0,169	0,043	1,496
Adjusted R^2	0,070		0,143		0,104	
F-statistic	2,263		3,802		2,961	
AIC	-0,643		5,901		1,035	
SIC	-0,430		6,113		1,247	

Table 6. Vector autoregression estimates for Ripple

Variable	Ripple ΔPrice	t-stat	Ripple ΔTrend	t-stat	Ripple ΔVolume	t-stat
Ripple ΔPrice(-1)	-0,105	-1,283	-1,625	-0,940	0,477	2,311
Ripple ΔPrice(-2)	-0,004	-0,049	-2,282	-1,278	0,125	0,585
Ripple ΔPrice(-3)	-0,081	-0,966	-3,957	-2,246	0,054	0,255
Ripple ΔPrice(-4)	0,008	0,100	-0,729	-0,452	0,273	1,419
Ripple ΔTrend(-1)	0,022	6,651	0,252	3,547	0,036	4,199
Ripple ΔTrend(-2)	-0,002	-0,669	0,016	0,205	-0,008	-0,905
Ripple ΔTrend(-3)	0,006	1,545	0,168	2,160	0,020	2,175
Ripple ΔTrend(-4)	0,002	0,567	-0,247	-3,166	-0,007	-0,754
Ripple ΔVolume(-1)	0,092	2,846	0,906	1,334	-0,298	-3,671
Ripple ΔVolume(-2)	0,021	0,614	0,902	1,244	-0,268	-3,093
Ripple ΔVolume(-3)	-0,017	-0,491	0,793	1,087	-0,181	-2,072
Ripple ΔVolume(-4)	0,038	1,171	0,415	0,614	-0,192	-2,381
C	0,014	0,900	0,044	0,138	0,054	1,393
Adjusted R^2	0,205		0,137		0,156	
F-statistic	5,334		3,674		4,113	
AIC	-0,190		5,908		1,658	
SIC	0,022		6,120		1,871	

Variable	Ripple ΔPrice	t-stat	Bitcoin ΔTrend	t-stat	Ripple ΔVolume	t-stat
Ripple ΔPrice(-1)	-0,022	-0,258	1,140	0,554	0,696	3,268
Ripple ΔPrice(-2)	0,119	1,396	-1,867	-0,904	0,345	1,614
Ripple ΔPrice(-3)	-0,013	-0,158	-2,179	-1,071	0,122	0,578
Ripple ΔPrice(-4)	-0,083	-1,099	1,962	1,074	0,118	0,624
Bitcoin ΔTrend(-1)	-0,008	-2,750	0,033	0,464	0,008	1,030
Bitcoin ΔTrend(-2)	0,007	2,366	-0,003	-0,040	0,018	2,408
Bitcoin ΔTrend(-3)	0,012	3,841	-0,012	-0,161	0,009	1,218
Bitcoin ΔTrend(-4)	0,006	1,874	-0,184	-2,362	0,003	0,340
Ripple ΔVolume(-1)	0,051	1,504	-0,792	-0,966	-0,391	-4,610
Ripple ΔVolume(-2)	-0,022	-0,607	1,118	1,267	-0,302	-3,307
Ripple ΔVolume(-3)	-0,028	-0,783	0,341	0,387	-0,213	-2,339
Ripple ΔVolume(-4)	0,029	0,860	-0,153	-0,189	-0,207	-2,469
C	0,014	0,886	0,036	0,095	0,053	1,331
Adjusted R^2	0,142		0,000		0,097	
F-statistic	3,783		0,999		2,808	
AIC	-0,114		6,264		1,726	
SIC	0,098		6,476		1,938	

Variable	Ripple ΔPrice	t-stat	Ethereum ΔTrend	t-stat	Ripple ΔVolume	t-stat
Ripple ΔPrice(-1)	-0,005	-0,056	2,989	1,249	0,632	3,120
Ripple ΔPrice(-2)	0,110	1,270	3,068	1,256	0,195	0,940
Ripple ΔPrice(-3)	-0,063	-0,737	3,920	1,627	-0,059	-0,287
Ripple ΔPrice(-4)	-0,163	-2,047	-2,873	-1,282	-0,046	-0,240
Ethereum ΔTrend(-1)	0,000	-0,135	0,054	0,749	0,018	2,888
Ethereum ΔTrend(-2)	0,003	1,132	-0,267	-3,695	0,015	2,454
Ethereum ΔTrend(-3)	0,010	3,634	0,214	2,891	0,011	1,728
Ethereum ΔTrend(-4)	0,006	2,062	0,012	0,156	-0,001	-0,116
Ripple ΔVolume(-1)	0,045	1,279	-1,052	-1,050	-0,397	-4,676
Ripple ΔVolume(-2)	-0,028	-0,716	-0,761	-0,703	-0,271	-2,953
Ripple ΔVolume(-3)	-0,032	-0,846	-0,155	-0,145	-0,170	-1,878
Ripple ΔVolume(-4)	0,047	1,369	-0,536	-0,555	-0,183	-2,233
C	0,016	0,981	-0,015	-0,032	0,059	1,520
Adjusted R^2	0,083		0,106		0,127	
F-statistic	2,518		2,989		3,452	
AIC	-0,048		6,629		1,692	
SIC	0,164		6,841		1,904	

But what causes the investor sentiment´s changes? For the Bitcoin, it can be seen that its investor sentiment is strongly affected by its own price development as the results show that price changes have a statistically significant positive effect with lags of one and four. The sign changes for lags of two and three, but the results are not statistically significant. Bitcoin´s investor attention is not affected by the price development of Ethereum and Ripple as the results are insignificant for all of the lags. This signals that the returns of smaller cryptocurrencies do not attract more attention to Bitcoin. Instead, the attention grows from its own returns which has a spillover effect to the attention of Ripple.

Ethereum´s investor sentiment is not affected by the price development of Bitcoin, as all of the results are insignificant. Its own price development has a surprising effect as the lags of one to three have an insignificant positive effect when the fourth lag has a statistically significant negative effect. The results are insignificant for all of the lags of Ripple. These results suggest that Ethereum´s investor attention is not linked to the returns of Bitcoin and Ripple. The results for trading volume are similar as none of the cryptocurrencies trading volume´s are able to predict investor attention to Ethereum. All in all, the results suggest that the investor attention of Ethereum is not affected much by the returns or trading volumes of the selected cryptocurrencies.

Ripple´s investor sentiment experiences similar results as its price change as Bitcoin´s price has a statistically significant positive relationship for the lags of two and three as the first lag has a negative relationship which is statistically insignificant. Surprisingly, Ethereum´s price development does not have a statistically significant effect on the investor sentiment of Ripple. However, similar effects can be seen as the relationship is negative for lags of one, three and four as the second lag has a positive effect. Ripple´s own price development has a negative effect through all of the lags being statistically significant for the third lag, showing that the price change does not increase attention for Ripple. In addition, the investor attention shows some signs of autocorrelation as its own first lag has a statistically significant positive effect on its self. The results for Ripple´s investor sentiment shows that the price development of Bitcoin mostly drives it with a gap week, this is supported by the adjusted R^2 as it is highest for the attention of Bitcoin.

Table 7. Granger causality

Dependent variable: Bitcoin ΔPrice				Dependent variable: Bitcoin ΔTrend				Dependent variable: Bitcoin Δvolume			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
Bitcoin ΔTrend	7,122	4	0,130	Bitcoin ΔPrice	28,672	4	0,000	Bitcoin ΔPrice	26,044	4	0,000
Bitcoin ΔVolume	0,503	4	0,973	Bitcoin ΔVolume	2,047	4	0,727	Bitcoin ΔTrend	28,619	4	0,000
All	8,627	8	0,375	All	30,088	8	0,000	All	70,915	8	0,000
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
Ethereum ΔTrend	4,951	4	0,292	Ethereum ΔPrice	1,919	4	0,751	Bitcoin ΔPrice	25,964	4	0,000
Bitcoin ΔVolume	1,847	4	0,764	Ethereum ΔVolume	2,812	4	0,590	Ethereum ΔTrend	27,796	4	0,000
All	6,439	8	0,598	All	4,775	8	0,781	All	69,932	8	0,000
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
Ripple ΔTrend	13,274	4	0,010	Ripple ΔPrice	3,375	4	0,497	Bitcoin ΔPrice	34,162	4	0,000
Bitcoin ΔVolume	1,155	4	0,885	Ripple ΔVolume	4,369	4	0,358	Ripple ΔTrend	4,832	4	0,305
All	14,826	8	0,063	All	6,336	8	0,610	All	42,526	8	0,000

Dependent variable: Ethereum ΔPrice				Dependent variable: Ethereum ΔTrend				Dependent variable: Ethereum ΔVolume			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
Ethereum ΔTrend	8,097	4	0,088	Ethereum ΔPrice	15,188	4	0,004	Ethereum ΔPrice	10,821	4	0,029
Ethereum ΔVolume	1,694	4	0,792	Ethereum ΔVolume	0,441	4	0,979	Ethereum ΔTrend	43,829	4	0,000
All	10,227	8	0,250	All	19,472	8	0,013	All	64,623	8	0,000
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
Bitcoin ΔTrend	7,351	4	0,118	Bitcoin ΔPrice	7,759	4	0,101	Ethereum ΔPrice	16,319	4	0,003
Ethereum ΔVolume	1,540	4	0,820	Bitcoin ΔVolume	9,178	4	0,057	Bitcoin ΔTrend	6,083	4	0,193
All	9,473	8	0,304	All	17,900	8	0,022	All	23,521	8	0,003
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
Ripple ΔTrend	11,042	4	0,026	Ripple ΔPrice	7,262	4	0,123	Ethereum ΔPrice	16,871	4	0,002
Ethereum ΔVolume	1,549	4	0,818	Ripple ΔVolume	1,533	4	0,821	Ripple ΔTrend	6,461	4	0,167
All	13,203	8	0,105	All	10,515	8	0,231	All	23,932	8	0,002

Dependent variable: Ripple ΔPrice				Dependent variable: Ripple ΔTrend				Dependent variable: Ripple ΔVolume			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
Ripple ΔTrend	50,825	4	0,000	Ripple ΔPrice	6,506	4	0,164	Ripple ΔPrice	7,548	4	0,110
Ripple ΔVolume	11,643	4	0,020	Ripple ΔVolume	2,801	4	0,592	Ripple ΔTrend	22,950	4	0,000
All	59,071	8	0,000	All	7,843	8	0,449	All	34,175	8	0,000
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
Ethereum ΔTrend	18,785	4	0,001	Bitcoin ΔPrice	23,111	4	0,000	Ripple ΔPrice	10,128	4	0,038
Ripple ΔVolume	7,291	4	0,121	Bitcoin ΔVolume	3,558	4	0,469	Ethereum ΔTrend	15,888	4	0,003
All	25,935	8	0,001	All	30,783	8	0,000	All	26,741	8	0,001
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
Bitcoin ΔTrend	33,185	4	0,000	Ethereum ΔPrice	6,406	4	0,171	Ripple ΔPrice	12,923	4	0,012
Ripple ΔVolume	6,069	4	0,194	Ethereum ΔVolume	2,011	4	0,734	Bitcoin ΔTrend	9,014	4	0,061
All	40,828	8	0,000	All	9,143	8	0,330	All	19,504	8	0,012

The granger causality test confirms our earlier results for Bitcoin´s price as it is not affected by its own investor sentiment or the investor sentiment of Ethereum. However, Ripple´s investor sentiment has an effect on it at the 10% significance level. The investor sentiment proxy for Bitcoin is strongly affected by its own price development as the other two cryptocurrencies do not have a statistically significant effect. Showing that Bitcoin and its investor attention have a unidirectional relationship.

The results are similar for Ethereum´s price as its own investor sentiment proxy shows some evidence for granger cause at the 10% statistical significance and Ripple´s investor sentiment proxy granger causes Ethereum´s returns at the 5% statistical significance. However, Bitcoin´s investor sentiment proxy does not show statistically strong evidence for granger causing Ethereum returns. These results are in line with the earlier findings. Also, similar results are found for the investor attention proxy of Ethereum as its own price development is statistically significant as the other two currencies are not. Interestingly, the average weekly volume change of Bitcoin is almost statistically significant for Ethereum´s investor sentiment. The results show some evidence for a bidirectional relationship between Ethereum´s price and its investor attention on a 10% significance level.

For Ripple´s price, the earlier findings are confirmed as all of the three investor sentiment proxies are statistically significant. The earlier findings for Ripple´s investor attention are strengthened as the results show that it is driven by the price development of Bitcoin as Ethereum and Ripple do not have statistically significant results. Showing that the price development of Ripple arises originally from the price development of Bitcoin.

The results for OLS-regression, Vector autoregression and Granger causality test suggest that Bitcoin´s returns cause investor attention to Ripple with lags of two to three. This investor attention is able to predict next week´s returns for Bitcoin and Ethereum. This effect can be seen as a product of representativeness and herding. The returns for Bitcoin boost the attention to Ripple as a smaller cryptocurrency as investors get more interested about other cryptocurrencies due to representativeness thinking that Bitcoin´s returns predict future returns in Ripple and start searching information about it. This has effect to the returns of Ripple and some effect to the prices of Bitcoin and Ethereum, showing evidence for attention induced returns which spillover originally from Bitcoin to Ripple and via Ripple´s investor attention back to the returns of Bitcoin and Ethereum. This effect can also be noticed in the vector autoregression as Ripple´s returns can be predicted by the lags of two and three of the Bitcoin investor attention which can be predicted by the returns of Bitcoin by a lag of one.

The delayed effect on investor attention in the cryptocurrency market has also been found by Sovbetov (2018) as he suggests that it is a significant factor for pricing in long-term time periods together with price trend, trading volume and volatility. These results agree with the findings of Corbet et al. (2018) and Ji et al. (2019) as we are able to show that Bitcoin sends shocks to the cryptocurrency market. It transfers at least partly from investor attention to returns of other cryptocurrencies originating back to its own returns due to herding as shown by Kallinterakis and Wang (2019).

As earlier studies about predicting cryptocurrency returns via investor sentiment proxied by Google Trend data has only considered using the search word of particular cryptocurrency or search words “Bitcoin” and “Cryptocurrency” predicting other cryptocurrencies returns they might have missed underlying information about the bullishness of the cryptocurrency markets sentiment as well as timing. Kallinterakis and Wang (2019) show that herding originates from smaller cryptocurrencies herding towards larger cryptocurrencies. Based on the result of this paper it seems that this herding can be caught by the investor attention of a smaller cryptocurrency, Ripple, which then represents the bullishness of the overall market which translates to the returns of larger cryptocurrencies Bitcoin and Ethereum. It is important to note that the investor attention towards Ripple is not caused by its own returns which can be observed in the two larger cryptocurrencies, Bitcoin and Ethereum. Instead, the investor attention is driven by Bitcoin´s returns. This process is similar to the results of Kristoufek (2013) as Bitcoin´s own investor attention drives the returns of Bitcoin, and the investor attention is driven by the returns of Bitcoin. As the market has become more efficient this relationship has disappeared (Eom et al. 2019; Bleher & Dimpfl 2019a) but the overall attention induced pricing can be observed through the investor attention of a smaller cryptocurrency. This suggests that the market is not as efficient as thought as attention induced pricing can still be observed in the cryptocurrency market.

Thus, these results also provide evidence for the inefficiency of the cryptocurrency market during the studied time period. These findings agree with the results of Kyriazis (2019), Urquhart (2016), and Charfeddine and Maouchi (2019) as we are able to show that it is possible to predict the future returns of the selected cryptocurrencies by using an investor sentiment proxy showing evidence for inefficient market behaviour.

6.3 Robustness

To test the robustness of the results, the sample is divided into two sub-samples: 1st of January 2016 – 8th of April 2018 and 9th of April 2018 - 29th December 2019. In addition, the multiple OLS-regression of equation (6) is completed. The results for robustness test are presented in Tables 8 and 9, where Table 8 presents the results for the first subsample as the latter for the second subsample.

The results for the first subsample confirm our earlier findings of individual regressions as the signs and effects are identical to the results of table three with the exception of the results of Ripples returns as Ethereum is statistically significant the sign staying the same.

Table 8. OLS-regression estimates for the first subsample

Dependent variable:	Bitcoin ΔPrice	Dependent variable:	Ethereum ΔPrice	Dependent variable:	Ripple ΔPrice
C	0,023**	C	0,046**	C	0,035
	(2,335)		(2,196)		(1,580)
Bitcoin ΔTrend	0,001	Bitcoin ΔTrend	-0,009***	Bitcoin ΔTrend	-0,004**
	(0,254)		(-4,834)		(-2,504)
Ethereum ΔTrend	0,000	Ethereum ΔTrend	0,007***	Ethereum ΔTrend	-0,005**
	(-0,118)		(4,453)		(-2,230)
Ripple ΔTrend	0,005***	Ripple ΔTrend	0,003**	Ripple ΔTrend	0,021***
	(3,937)		(2,175)		(5,083)
Bitcoin ΔVolume	0,034	Ethereum ΔVolume	0,043	Ripple ΔVolume	0,078**
	(0,829)		(1,368)		(2,513)
Adjusted R^2	0,0407	Adjusted R^2	0,1187	Adjusted R^2	0,2429
Prob(F-statistic)	0,0715	Prob(F-statistic)	0,0012	Prob(F-statistic)	0,0000
Durbin-Watson	2,1160	Durbin-Watson	2,0353	Durbin-Watson	2,1406

Table 8 reports the OLS-regression estimates where the coefficient is reported next to the variable and the t-stat for the coefficient is located under the coefficient.

*** Statistical significance at the 1% level
** Statistical significance at the 5% level
* Statistical significance at the 10% level

Table 9. OLS-regression estimates for the second subsample

Dependent variable:	Bitcoin ΔPrice	Dependent variable:	Ethereum ΔPrice	Dependent variable:	Ripple ΔPrice
C	0,002	C	-0,011	C	-0,007
	(0,190)		(-0,732)		(-0,581)
Bitcoin ΔTrend	0,004	Bitcoin ΔTrend	-0,001	Bitcoin ΔTrend	-0,012
	(0,560)		(-0,084)		(-1,833)
Ethereum ΔTrend	0,001	Ethereum ΔTrend	-0,001	Ethereum ΔTrend	-0,001
	(0,512)		(-0,176)		(-0,251)
Ripple ΔTrend	0,007	Ripple ΔTrend	0,019	Ripple ΔTrend	0,081***
	(1,113)		(1,557)		(3,187)
Bitcoin ΔVolume	-0,005	Ethereum ΔVolume	0,048	Ripple ΔVolume	0,044
	(-0,081)		(0,531)		(1,504)
Adjusted R^2	-0,021	Adjusted R^2	-0,026	Adjusted R^2	0,228
Prob(F-statistic)	0,716	Prob(F-statistic)	0,790	Prob(F-statistic)	0,000
Durbin-Watson	1,943	Durbin-Watson	2,016	Durbin-Watson	2,393

Table 9 reports the OLS-regression estimates where the coefficient is reported next to the variable and the t-stat for the coefficient is located under the coefficient.

*** Statistical significance at the 1% level
** Statistical significance at the 5% level
* Statistical significance at the 10% level

The results for the second subsample differ from the earlier findings as to the ability to predict near-term future returns for Bitcoin and Ethereum disappears and the adjusted R^2s are negative for both of the regressions showing absolutely no ability to predict the future returns. Interestingly, the results for Ripple deviate from Bitcoin and Ethereum as its own investor attention has statistically significant ability to predict future returns. However, the investor attention proxies of Bitcoin and Ethereum are not statistically significant the same applying to the trading volume of Ripple.

Comparing the results for the two subsamples suggest that the cryptocurrency market became more mature and efficient after the bubble period and sell-off stage as the ability to predict future returns disappears or becomes less significant based on the coefficients, t-stats and R^2s. These results agree with the earlier findings as its noted that the cryptocurrency market becomes more efficient as time passes (Kyriazis 2019; Urquhart 2016; Tran and Leivik 2019) and that the prediction power of investor sentiment is more prone during the bubble period (Kraaijeveld & Medt 2020; Rognone et al. 2020). Interestingly it seems that the market capitalization has some effect on this transformation. As the smallest cryptocurrency, Ripple stays somewhat inefficient compared to Bitcoin and Ethereum as its investor attention has a higher coefficient in the latter subsample both of t-statistics being strongly statistically significant. This suggests that the cryptocurrency market behaves similarly to the stock market as more speculative and riskier assets are more prone to investor sentiment compared to more mature assets (Baker & Wurgler 2007).

7 Conclusion

This thesis investigates the predictive power of investor attention towards cryptocurrency returns by examining Bitcoin, Ethereum and Ripple from 2016 to 2019. Additionally, the interconnections of the cryptocurrency market are studied as well as what causes attention to cryptocurrencies. The study is completed by completing OLS regressions, vector autoregressions and Granger causality tests. Further, the OLS results are reviewed by robustness checks dividing the sample into two subsamples and adding all of the investor attention proxies to the regression for all of the three cryptocurrencies.

The previous studies about cryptocurrencies have not reached a single conclusion about investor attention´s predictive powers. The results vary between studies and as the cryptocurrency market has shown to become more efficient by time (Tran & Leivik 2019; Vidal-Tomás & Ibañez 2018; Urquhart 2016; Kyriazis 2019) the underlying market dynamics may also change. Further, the number of cryptocurrencies has increased year by year, and thus the results may differ between cryptocurrencies as they are in different market periods of their development. Cryptocurrencies have been shown to be interconnected and that the relationships develop and vary by time (Corbet et al. 2018; Ji et al. 2019; Ferreira & Pereira 2019). It has been shown that the attention to cryptocurrencies can be predicted by the returns of cryptocurrencies (Kristoufek 2013; Urquhart 2018). In addition, the cryptocurrency market has been shown to be prone to herding (Bouri et al. 2019; Vidal-Tomás et al. 2019; Kallinterakis & Wang 2019).

The results of this thesis add to the previous literature by showing that investor attention has predictive powers to the cryptocurrency returns, the relationship being statistically significant for Bitcoin and Ethereum for the first subsample. Contrary, Ripple´s investor attention maintains the predictive power for both samples showing some evidence that the smaller cryptocurrencies are more inefficient than, the bigger cryptocurrencies. These results follow the earlier findings for investor sentiment as smaller and more speculative assets has been shown to be more prone to the investor sentiment (Baker & Wurgler 2007). Further, it adds evidence to the earlier findings that cryptocurrencies mature by time as the results of the main OLS regression significantly differ between the sub-samples showing evidence that Bitcoin and Ethereum became more efficient after the bubble period of cryptocurrencies.

The interconnections of the cryptocurrency market are shown to exist as Ripple´s investor attention is the best predictor of future returns for all of the sample´s cryptocurrencies, instead of Bitcoin´s investor attention. However, this effect diminishes in the after-bubble period. The attention to the particular cryptocurrency is shown to be caused by its own returns as well as Bitcoin´s returns. As the attention to Ripple´s investor attention is shown to be caused by the returns of Bitcoin, it can be stated that Bitcoin sends attention shocks to other cryptocurrencies due to herding and representativeness which reflects back to the prices of cryptocurrencies—showing some evidence that smaller cryptocurrencies herd towards bigger cryptocurrencies via investor sentiment. The attention moves slowly in the market, and it is shown to take weeks to transfer, which supports earlier findings in the cryptocurrency literature (Sovbetov 2018). Further, it is also shown that Ethereum is more of a shock receiver than a sender as its investor attention has the worst predictive powers of all of the investor attention proxies.

As the market dynamics change by time in the cryptocurrency market, the behaviour of sentiment and returns vary in time. Thus, future research should be conducted in a broader time period after the bubble period as the earlier results may differ due to different market phase and maturity of a particular cryptocurrency. In addition, the number of analyzed cryptocurrencies should be increased and cryptocurrency specific investor attention spill-overs should be analyzed as this study show some evidence for predicting future returns by using smaller cryptocurrency attention proxies. This study also adds evidence to the earlier literature that in future research, cryptocurrencies should be studied separately as the behaviour of cryptocurrencies differs between cryptocurrencies, time periods and market phases.

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Appendix

Appendix 1. Lag order selection criteria. Where * denotes the suggested lag order by the criterion: sequential modified LR test statistic (LR), Final predition error (FPE), Akaike information criterion (AIC), Schwarz indormation criterion (SC), and Hannan-Quinn information criterion (HQ).

Bitcoin - Bitcoin

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-460,57	NA	0,02	4,66	4,71	4,68
1	-427,66	64,48	0,02	4,42	4,612*	4,50*
2	-416,61	21,33	0,02	4,40	4,75	4,54
3	-407,39	17,51	0,02	4,40	4,89	4,60
4	-397,77	18,00*	0,02*	4,39*	5,04	4,65
5	-391,53	11,48	0,02	4,42	5,21	4,74
6	-383,54	14,45	0,02	4,43	5,37	4,81
7	-378,55	8,88	0,02	4,47	5,56	4,91
8	-369,16	16,42	0,02	4,46	5,71	4,97

Ethereum - Ethereum

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-671,06	NA	0,18	6,77	6,82	6,79
1	-638,41	63,99	0,14	6,54	6,74*	6,62*
2	-624,80	26,26	0,13	6,49	6,84	6,63
3	-614,24	20,07	0,13	6,47	6,97	6,68
4	-602,22	22,47	0,13*	6,44*	7,09	6,71
5	-595,31	12,70	0,13	6,47	7,26	6,79
6	-585,19	18,32*	0,13	6,45	7,40	6,84
7	-580,53	8,28	0,13	6,50	7,59	6,94
8	-575,40	8,97	0,14	6,54	7,78	7,04

Bitcoin - Ripple

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-442,79	NA	0,02	4,48	4,53*	4,50
1	-421,92	40,90	0,02	4,36	4,56	4,44*
2	-410,51	22,01	0,02	4,34	4,68	4,48
3	-401,56	17,02	0,02	4,34	4,83	4,54
4	-381,63	37,25	0,01*	4,23*	4,87	4,49
5	-378,38	5,98	0,01	4,29	5,08	4,61
6	-367,26	20,11*	0,01	4,26	5,21	4,65
7	-361,26	10,67	0,01	4,29	5,39	4,74
8	-353,29	13,95	0,01	4,30	5,55	4,81

Ethereum - Bitcoin

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-627,94	NA	0,11	6,34	6,39*	6,36
1	-611,22	32,76	0,11*	6,26*	6,46	6,34*
2	-603,03	15,80	0,11	6,27	6,62	6,41
3	-596,55	12,31	0,11	6,30	6,79	6,50
4	-590,11	12,05	0,11	6,32	6,97	6,58
5	-586,16	7,26	0,12	6,37	7,17	6,69
6	-575,97	18,44*	0,12	6,36	7,30	6,74
7	-568,53	13,22	0,12	6,38	7,47	6,82
8	-561,63	12,07	0,12	6,40	7,64	6,90

Ripple - Ripple

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-743,30	NA	0,36	7,50	7,55	7,52
1	-703,11	78,77	0,27	7,19	7,39*	7,27*
2	-696,63	12,50	0,27	7,21	7,56	7,35
3	-684,95	22,18	0,27	7,19	7,68	7,39
4	-671,40	25,34	0,25	7,14	7,79	7,40
5	-657,92	24,78	0,24	7,09	7,89	7,42
6	-639,76	32,85	0,22	7,00	7,95	7,38
7	-627,87	21,16*	0,21*	6,97*	8,07	7,42
8	-622,08	10,13	0,22	7,01	8,25	7,51

Bitcoin - Ethereum

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-500,01	NA	0,03	5,06	5,10*	5,08
1	-478,27	42,59	0,03	4,93	5,13	5,01
2	-458,91	37,37	0,02	4,82	5,17	4,96*
3	-448,73	19,32*	0,02*	4,81*	5,31	5,01
4	-440,46	15,47	0,02	4,82	5,46	5,08
5	-432,76	14,17	0,03	4,83	5,63	5,15
6	-425,25	13,58	0,03	4,85	5,79	5,23
7	-423,80	2,59	0,03	4,92	6,01	5,36
8	-418,31	9,59	0,03	4,96	6,20	5,46

Ethereum - Ripple

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-609,38	NA	0,09	6,15	6,20*	6,17
1	-588,04	41,84	0,08	6,03	6,23	6,11*
2	-576,35	22,56	0,08	6,00	6,35	6,14
3	-571,20	9,77	0,08	6,04	6,54	6,24
4	-556,80	26,92*	0,08*	5,99*	6,63	6,25
5	-554,16	4,86	0,09	6,05	6,85	6,37
6	-546,30	14,22	0,09	6,06	7,01	6,45
7	-538,83	13,28	0,09	6,08	7,17	6,52
8	-533,41	9,48	0,09	6,11	7,36	6,62

Ripple - Ethereum

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-815,32	NA	0,75	8,22	8,27	8,24
1	-790,80	48,06	0,64	8,07	8,27*	8,15*
2	-776,19	28,18	0,61	8,01	8,36	8,15
3	-763,54	24,03	0,58	7,98	8,47	8,18
4	-748,84	27,49	0,55	7,92	8,56	8,18
5	-740,17	15,95	0,55	7,92	8,72	8,24
6	-725,84	25,92	0,53*	7,87*	8,81	8,25
7	-721,03	8,55	0,55	7,91	9,00	8,35
8	-708,54	21,84*	0,53	7,87	9,12	8,38

Ripple - Bitcoin

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-760,69	NA	0,47	7,75	7,80	7,77
1	-736,88	46,64	0,40	7,60	7,80*	7,68*
2	-727,13	18,81	0,40	7,60	7,95	7,74
3	-717,55	18,19	0,40	7,59	8,09	7,79
4	-703,87	25,55	0,38	7,54	8,19	7,80
5	-686,10	32,67	0,35	7,45	8,25	7,78
6	-674,03	21,81	0,34	7,42	8,37	7,81
7	-662,74	20,05	0,33	7,40	8,50	7,84
8	-651,45	19,73*	0,32*	7,38*	8,63	7,88