ANALYSIS OF CRYPTOCURRENCIES PRICE FORMATION

What can the price formation of cryptocurrency explain?

UNIVERSITY OF TWENTE.

Master thesis - Analysis of cryptocurrencies price formation

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ABSTRACT

Surprisingly little is written regarding cryptocurrencies in the academic literature (Cheung, et al., 2015) and most information available is merely regarding Bitcoin. Resulting in a lack of knowledge and consistency regarding important, investing related, questions. Such as if (traditional) pricing or valuation techniques apply to cryptocurrencies, what factors influence cryptocurrencies and what differences are can be recognized among cryptocurrencies? Therefore the following central research question and corresponding sub questions are created to explain and understand the price movement of cryptocurrencies:

What can the price movement of cryptocurrencies explain?
What pricing theories can be applied to cryptocurrencies?
What factors can explain the price movement of cryptocurrencies?

To answer these questions three traditional pricing techniques (cost-based, supply and demand and technical analysis) are elaborated upon and included in a testable model. Two years of data of five cryptocurrencies is adopted to test the theoretical model. Cryptocurrencies experience since their origin phases of vast development (hence growth) and relatively stable phases. I therefore distinguished between an ordinary year and a year of rapid growth.

This research distinguishes itself from previous research as it investigates multiple cryptocurrencies rather than Bitcoin only, all included cryptocurrencies are investigated on individual level. Furthermore an accumulated data set is analysed while mitigating the dominance of Bitcoin. Additionally some remedies are applied to reduce the focus on U.S. influential factors, thus move the focus to global influential factors.

The results of testing two (annual) models show that cryptocurrencies price movement can best be explained by volume during years of rapid growth. While a combination of both volume and public interest or attention related factors can best be used during a normal year. Whereas volume is a factor that is part of the technical analysis technique, public interest is a factor that is part of the supply and demand technique. I therefore suggest to use a combination of both techniques to explain cryptocurrencies price movement. Additionally I found out that price movement can best be explained when not using daily, but weekly data.

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1 INTRODUCTION

Bitcoin and alternative cryptocurrencies (altcoins) seem attractive for investment due to their rapid increase in price. However, a lack of understanding regarding cryptocurrencies' characteristics cause difficulties and complicates choosing among them. Cryptocurrencies are software protocols that can include certain characteristics such as; quick payments, safe payments, smart contracts, record keeping and above all daily transactions (Böhme, Christin, Edelman, & Moore, 2015; Wang & Vergne, 2017). Cryptocurrencies distinguish themselves from ordinary currencies due to their decentralization (Nakamoto, 2008; Böhme, et al, 2015; Hayes, 2017; Wang & Vergne, 2017; Blau, 2018). There are, yet, no banks or governmental organizations involved in the transaction process, a more extensive explanation of this process can be found in paragraph 2.1. In 2017, Bitcoin and altcoins have increased in price more than 3100%. However, cryptocurrencies are characterized as highly volatile and have experienced multiple bubbles (Cheung, Roca, & Su, 2015; Blau, 2018). Additionally Chatterjee, Son, Ghatak, Kumar and Khari (2017) state that there is no scientific model with sufficient predictive power to predict how cryptocurrencies will react to certain circumstances. Besides, between December 2016 and December 2017 more than 700 new currencies emerged (Coinmarketcap, 2017), a total increase of 216%. To be able to invest in cryptocurrencies it is useful to create a better understanding of what factors determine their price and if there are differences in these factors among the different cryptocurrencies (Wang & Vergne, 2017).

Despite the media coverage that cryptocurrencies have earned, surprisingly little is written in the academic literature (Cheung, et al., 2015) and most information available is merely regarding Bitcoin. For example, Scopus.com (a database for academic articles) includes 226 articles regarding cryptocurrency and 873 regarding Bitcoin on the 7th of December 2017. On this date Scopus.com includes more than 26.000 articles regarding 'ordinary' currencies. Bitcoin's dominance in articles is presumably caused by its dominance during the emerge of cryptocurrency. Whereas Bitcoin held between 74% to 96% of the total market capitalization during the period from April 2013 until December 2017 (Coinmarketcap, 2017). Notwithstanding, little is written about the price formation of cryptocurrencies. Multiple authors state that is difficult to assess the intrinsic value of cryptocurrency. It is for example unknown if (traditional) pricing or valuation theories apply to cryptocurrencies. Resulting in scattered research with no clear consensus. Hence, two streams of research can be recognized that have not been linked while using a single valuation theory.

The first stream of research regarding the influence of technical characteristics is represented by Cheung, et al. (2015), Ciaian, Rajcaniova and Kancs (2016), Wang and Vergne (2017) and Blau (2018). Cheung, et al. (2015) and Blau (2018) question if cryptocurrencies are commodities, currencies or assets. Ciaian, et al. (2016) at the other hand state that Bitcoin experienced bubbles and therefore state that Bitcoin is too volatile to be used as a currency in the short run. While Wang and Vergne (2017) state that Bitcoin and four altcoins are strictly neither a commodity nor a currency. Nevertheless, a clear definition for the cryptocurrencies and a comparison among cryptocurrencies remain unexplained. Moreover the influence of this characteristic on the price is not specified. In addition, the effect of the blockchain authorization on cryptocurrencies' price requires further research. This characteristic seems most important taking into account the fact that half of the top 20 cryptocurrencies have a divergent blockchain authorization techniques on December 30, 2017 (Coinmarketcap, 2017). Wang and Vergne (2017) show that funding for technical innovation relates positively with price. However, although several implications are stated, no empirical evidence is given for their influence on the price. This leaves room for further research

The second stream of research is focussed on non-technical influencers, such as attention, number of transactions and macroeconomic factors. Multiple authors wrote about these three factors but they could not find common ground. For instance Pakrou and Amir (2016) recognize four (cultural) factors that influence the intention to use cryptocurrencies. On the other hand, Ciaian, et al. (2016)

and Wang and Vergne (2017) explain the price fluctuations based on (media) attention and number of transactions in, mainly, Bitcoin. Furthermore Ciaian, et al. (2016) indicate that Bitcoin is not influenced by macro financial developments, which is claimed before by Karasik and Kuzmina (2015). However, no empirical evidence is given for altcoins. Again, a lack of consensus leaves room for further research.

To conclude, a lack of consistency regarding influential factors leaves room for further research, especially towards altcoins. Therefore the following central research question is created to explain and understand the price movement of cryptocurrencies:

What can the price movement of cryptocurrencies explain?

Furthermore, it is unclear of a traditional pricing theory can be used to, partially, explain cryptocurrencies' price movement. Additionally, theory regarding the issues described above form the basis for this report. Hence, a theoretical framework is written regarding existing techniques to explain price movements. Each pricing theory consists of multiple underlying factors, as described in chapter 3. Additionally, this research explores factors that influence cryptocurrencies. Consequently, two sub question are created to explore whether current pricing theories can be applied to cryptocurrencies:

What pricing theories can be applied to cryptocurrencies?
What factors can explain the price movement of cryptocurrencies?

This study contributes to the literature in two important ways, both technological and economical. Previous research did not distinguish cryptocurrencies upon technical characteristics to determine their success. Developers and investors can use this knowledge to improve their currency or diversify their portfolio. Additionally non-technical (market) factors are investigated. Hence, this report contributes especially to the investment sector as both technical and non-technical (market) influencers are taken into account. This research can result in more insights for profitable and/or less risky investment strategies.

Some considerations regarding academic literature are made to secure the quality of this report. First of all, academic literature is only used if found via Scopus.com. Scopus.com contains only high quality content due to its independent 'Content Selection and Advisory Board' (Elsevier, 2017). Secondly, certain search queries are used based upon the sub questions, the used search query is displayed in the source matrix which can be found in appendix 6.2. Subsequently all remaining sources are sorted on date (newest) taking into account the newness of this subject. Thereafter, all literature is reviewed bottom down by the researcher. Theories stated in relatively old articles (2015 and before) are only consulted if these are confirmed in 2016 or later, this can also be found in appendix 6.2. An indication is given once deviated from this strategy. Besides, statements made in articles are reviewed to see if these are supported by either empirical evidence or previous research. For example, Karasik and Kuzmina (2015, p. 869) claim that cryptocurrency exchange rate does not depend on macroeconomic conditions and reason why this is the case. While Ciaian, et al. (2016) claim that the price of Bitcoin does not depend on macroeconomic conditions based on their empirical data combined with three previous studies. Obviously, the statement of Karasik and Kuzmina (2015) is questionable and therefore not used. The statement of Ciaian, et al. (2016) on the other hand seems applicable and is therefore used in this report.

The remaining part of the article is structured as followed. Section two provides a theoretical framework, including background information about cryptocurrency and valuation theories. Then, in chapter three a methodological approach of the research is proposed. Finally chapter four covers all practicalities of the research, such as the restrictions and limitations which the researcher must encounter, a comprehensive time frame and a provisional table of content.

2 CRYPTOCURRENCY

To create a better understanding of cryptocurrencies three aspects are elaborated upon. First of all, the origin and protocol are elaborated to be able to understand why cryptocurrencies exist. This section includes a brief technical explanation, advantages and disadvantages of cryptocurrencies. Secondly two technical characteristics are clarified to create better understanding of the diversity of the current cryptocurrencies. This might indicate what valuation technique is best suitable. Both blockchain authority and core purpose are elaborated.

Cryptocurrencies have little or unknown intrinsic value as is mentioned in the introduction. Ciaian, et al. (2016, p. 1803) states: "*Given that BitCoin is a fiat currency and thus intrinsically worthless, it does not have an underlying value derived from consumption or its use in production process (such as gold)*". Hayes (2017) agrees with Ciaian, et al., but claims that a bitcoin can have intrinsic value based upon its technical innovation. However, its intrinsic value is not as tangible such as the value of gold. Thus, little is known about how to measure the intrinsic value of cryptocurrency. Hence, intrinsic factors that could influence price movement are not discussed in this chapter, I leave this subject for further research. The influence on price movement of all origin and protocol, blockchain authority and nature is described throughout the corresponding sections.

Different search queries are used compare to those used in the introduction. Appendix 6.2 contains an overview of the literature used in this chapter. The same considerations are used throughout the report to maintain quality. Additionally the thesis of Bitcoin's creator, Satoshi Nakamoto, is consulted to obtain the required technical background information.

2.1 ORIGIN AND PROTOCOL

Bitcoin, created in 2008, was the first of the current cryptocurrencies. Bitcoin's creation included an open source protocol that contained its software: the blockchain. Since Bitcoin started with an open source software algorithm, multiple altcoins are based on Bitcoin's original code. Developers of altcoins usually add or modify certain characteristics to distinguish themselves, resulting in coins with different functions such as; quick payments, safe payments, smart contracts and record keeping (Böhme, Christin, Edelman, & Moore, 2015; Wang & Vergne, 2017). Currently, more than 1500 cryptocurrencies exist, all with different unique characteristics and development teams (Coinmarketcap, 2017).

The protocol of cryptocurrencies are based on cryptographic proof instead of trust. Transactions are executed, controlled and encrypted by affiliated computers within the peer-to-peer network instead by institutions or regulators (as for instance banks). These affiliated computers are called 'miners', since these mine or process the data for transactions. Miners are rewarded with newly minted coins or a transaction fee to encourage users to assist the network. For a transaction to take place, miners need the private keys of both the sender, the receiver and in some cases the previous owner of the coins. A private key is account specific decipher feature needed to decrypt a message to be able to read the transaction assignment. Subsequently, each miner creates a new encrypted string that is stored in a public accountant book that serves as proof-of-work, called the 'block'. Every consecutive encryption must start with a random section of the former encryption, called the 'chain'. Furthermore, Nakamoto (2008) increased security by adding a feature that randomly selects miners that solve the same encryption. Transactions are approved and executed when multiple miners have reached the same result. The blockchain and the random selection of miners, make fraud and flaws impossible without someone noticing it. Bitcoin and altcoins can thus be defined as encrypted currency or cryptocurrency. A visualisation of Bitcoin's blockchain protocol is displayed in figure 2.1. (Nakamoto, 2008; Böhme, et al, 2015; Hayes, 2017; Blau, 2018)

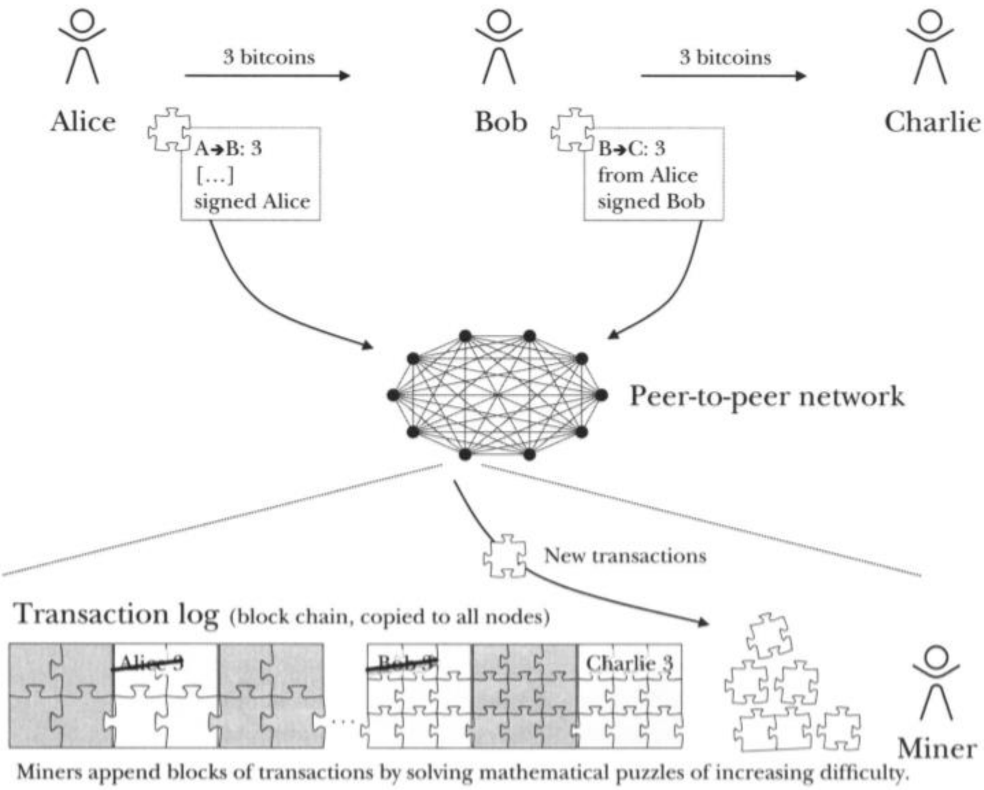

Figure 2.1: : Bitcoin's Approach to Transaction Flow and Validation. Retrieved from Böhme, et al. (2015).

Originally, cryptocurrencies were initiated to provide decentralized, peer-to-peer low cost and cross border transactions. Decentralized as within the meaning of not subject to a single source of power (governments, banks or multinationals). As described, most cryptocurrencies are not controlled or issued by a company, government or central authority but by a software algorithm. Due to this, large concentrations of power that could let a single organization take control are avoided. The peer-to-peer characteristic, which allows users to send money directly to another person (hence peer-to-peer), is a consequence of the decentralization of cryptocurrencies. This peer-to-peer characteristic allows cryptocurrencies to exclude other third parties that might benefit from transactions (such as PayPal or Visa), resulting in less costly transactions. Moreover, no third parties have full knowledge of payments made, which results in greater privacy for users. Additionally, some cryptocurrencies are known for their quick cross border transactions, since no bank or third party needs to approve a payment. Thus, most benefits of cryptocurrencies are derived from their decentralized authority system (or consequences of this). Several authors (Böhme, et al. 2015; Ciaian, et al. 2016; Chatterjee, et al. 2017; Hayes, 2017; Hong, 2017; Blau, 2018) agree unanimously about cryptocurrency's benefits as can be seen in appendix 6.2.

Nevertheless, some disadvantages regarding cryptocurrencies are also recognized. First of all, cryptocurrencies were attractive for criminal transactions due to the greater privacy that the cryptocurrency' protocol offers. Illicit activities ranging from money laundering to selling drugs became easier by the arrival of cryptocurrencies: "*One prominent example involved the online sale of narcotics including marijuana, prescription drugs, and benzodiazepines (a class of psychoactive drugs)*" (Böhme, et al., 2015, p. 222). A second disadvantage is the volatility of cryptocurrencies. Multiple authors point out that cryptocurrencies are highly volatile (Cheung, et al., 2015; Blau, 2018), including weekly changes of more than 30% that are not irregularities. Thirdly, the decentralized structure of cryptocurrencies is fragile after the arrival of prominent currency exchanges, mining pools and other service providers (Böhme, et al., 2015). BuyBitcoinWorldwide (2018) describes mining pools as "*groups of cooperating miners who agree to share block rewards in proportion to their contributed mining hash* *power*". Groups of cooperating miners who agreed to share block rewards in proportion to their contributed mining hash power. These intermediaries control such a significant proportion of coins or mining activities that they in fact can make demands or influence the direction of the developers. For example, Bitcoin's November 2017 hard fork (splitting of a currency into two different types of currencies) was called off due to a lack of consensus of the mining pools (Coindesk.com, 2017). This occurred while the contributors to the open source protocol believed it to be an improvement. Finally, some cryptocurrencies seem not (yet) suitable for consumer payments. Bitcoin in particular is irreversible, so it has no payback function such as some banks offer. Furthermore Bitcoin requires a vast amount of storage, which creates a large storage burden. Besides, Bitcoin is designed to process a transaction every 10 minutes, which is too slow for retail purposes. Lastly, Bitcoin is pseudonymous, not anonymous. Which means that users do not use their personal name, but a personal key. Thus, every payment can be traced back to a personal key (Böhme, et al., 2015). However, some currencies adjusted their protocol to address these problems. For example, Ethereum does offer smart contracts that allow payback features (Ethereum Foundation, 2018), IOTA created a different and most of all shorter block and therefore chain (Popov, 2017), Litecoin and Dash created faster payments (Litecoin Foundation, 2017; The Dash Network, 2018) and Monero created a blockchain with higher anonymity (The Monero Project, 2015). Additional, in-depth, technical characteristics regarding the method and protocol of how these blockchains function are beyond the scope of this paper.

2.2 BLOCKCHAIN AUTHORITY

Some cryptocurrencies use, despite their origin, other blockchain protocols that are not completely decentralized. Hence, different blockchain authorizations have emerged. Böhme, et al., (2015) and Wang and Vergne (2017) distinguish two types of blockchain authority; *decentralized currencies* and *partially decentralized currencies*. Whereas (original) decentralized cryptocurrencies always rely on miners (affiliated computers) to verify transactions, partially decentralized currencies often rely on a private verification process. Accordingly, every transaction, bookkeeping recording and remaining actions of decentralized cryptocurrencies can be realised by any individual around the world with the required equipment (special computers and software). Mostly decentralized cryptocurrencies on the other hand have their own transaction and bookkeeping software, which is only accessible for a select group of individuals. For example world's second largest cryptocurrency (December 30, 2017), Ripple (Coinmarketcap, 2017), has a team of developers (hence not open source) that aim for profit. Ripple uses a verification process that does not rely on mining to achieve consensus (Ripple Labs, 2017). Some of the partially decentralized currencies do not provide new minted coins as a reward for miners. These currencies, such as NEO and NEM, already function at their maximum supply by design.

Additionally, a distinction can be made based on how the difficulty the blockchain authority protocol. Hayes (2017) showed that the algorithm's difficulty influences the costs of cryptocurrencies. For example, the algorithm of Bitcoin allows a transaction every 10 minutes, if there are many transactions, the puzzle to solve by miners becomes easier, while if there are little transactions, the puzzle becomes more difficult (Nakamoto, 2008). Ripple at the other hand created a blockchain that is designed to be fast, a transaction occurs almost instantly and requires less computing power (Ripple Labs, 2017). For the purpose of this research the blockchain authorities are categorized into light, medium and heavy blockchains. Where 'light' is a blockchain that requires little computing power (less than 1 minute to process transaction), 'medium' requires average computing power (1-3 minutes) and 'heavy' requires more computing power (more than 3 minutes). Table 2.1 contains an overview of 5 cryptocurrencies and their blockchain authority. Notable is the number of 10 minutes required to hash a block using the Bitcoin protocol, whilst other are lower than 2.5 minutes.

Table 2.1: overview blockchain authorization per cryptocurrency. Retrieved from multiple online sources. Average block time in minutes is added, retrieved from (Bitinfocharts.com, 2018).

Decentralized	**Block time**	**Partially decentralized**	**Block time**
Bitcoin **(Nakamoto, 2008)**	Heavy (10)	Ripple (Ripple Labs, 2017)	Light (0.1)
Ethereum **(Ethereum Foundation, 2018)**	Light (0.5)	NEM (NEM.io Foundation ltd, 2018)	Light (0.8)
Litecoin **(Litecoin Foundation, 2017)**	Medium (2.5)		

Nevertheless, the extent of decentralized and the centralization caused by prominent currency exchanges, mining pools and other service providers might have an influence on costs and price. Chatterjee, et al. (2017) and Hayes (2017) provide evidence of the cost structure of Bitcoin (Hayes also for altcoins). Hayes suggest that ‘lighter’ blockchains need less computer power, thus consume less electricity. Thus, the difficulty of the blockchain is an explanatory for the cost-price of cryptocurrencies. Chatterjee, et al. (2017) and Hayes (2017) do not provide evidence regarding the influence on price. Additionally, Hayes (2017) suggest that when the mining process becomes more efficient (due to mining pools or technical progress), it lowers the costs and puts a negative pressure on the price. Furthermore, little is written about service providers and currency exchanges. However, the costs of transferring cryptocurrencies via an exchange often have a set percentage of transaction costs varying between .26% and .10% (Kraken, 2018; Binance, 2018). Fees for cryptocurrencies are usually lower as they vary between 0.22% and .002%. Whereas the fees of .22% only have been paid during periods of high volatility. 90% of the fees in 2017 was lower than .02% (Coindesk, 2018; Coinmarketcap, 2017).

2.3 NATURE OF CRYPTOCURRENCY

Little is written about the core characteristic of cryptocurrencies, are they commodities, currencies or assets? Theoretically a commodity can be defined as an economic good of any kind that is intended for sale or trade that has a specific economical value. The good keeps remains a commodity during its passage, sometimes through multiple owners, until it reaches its final economic destination. We then call it a consumption good (Menger, Klein, & Hayek, 2007). A currency, or coinage, is a generally accepted form of payment that has a set value. At first, traders used precious metals like gold and silver as currency. However, metal as a currency has proven to be very inconvenient: “*“When a person goes to market in Burma,” Bastian relates, “he must take along a piece of silver, a hammer, a chisel, a balance, and the necessary weights.”*” (Menger, et al., 2007, p. 281). Therefore, light minted coins and even notes with a specific value were issued. They keep their value as long as they are limited available and cannot be copied. Nevertheless, if the currency is made of a certain metal, let’s say silver, then it can be a commodity to. A silversmith can melt it and use it to forge a silver ring for instance. Tan and Low (2017), supported by the Radford paper (as cited in Tan & Low, 2017), agree with the theory described by Menger, et al. (2007). Hence, Tan and Low (2017) state that the intention of users determines if it is a currency or commodity. If a (large) group of individuals agrees to use matches as a form of payment (thus they generally accept it), it is a currency. As soon as one starts lighting fires with it, it is a commodity again. An asset can be defined as an (in)tangible economic resource held by an individual or firm to produce (positive) economic value, such as corporate bonds, preferred equity, stocks and other hybrid securities. Whereas it is often owned only (often the case for individuals), but it can also be controlled (by a firm or shareholder). Owners can exercise their influence to improve the value of the asset. For example, a shareholder of a large quarry has to knowledge to produce bricks of better quality for the same price. Utilizing this knowledge can result in higher sales or revenue, hence an increase in the value of the underlying asset (O'Sullivan & Sheffrin, 2003).

Several authors wrote about the nature of cryptocurrencies. Ciaian, et al. (2016) for instance suggest that cryptocurrencies are too volatile to be a currency, so cryptocurrencies are not (yet) able to able to keep their value as Menger, et al. (2007) suggested. However, Wang and Vergne (2017) suggestion of predicting value based upon technical purpose. Which is in line with the views of (Menger, et al., 2007) and Tan and Low (2017) who oppose that the user intention determines what a currency is. Hence, cryptocurrency owned by users via a wallet (thus are able to spend it) are more likely to be seen as currency. For example Dash offers a special wallet that can be installed on mobile devices with as sole purpose to pay at using QR codes (The Dash Network, 2018). While cryptocurrency owned by users via a trading platform, for example the same Dash coins owned via an exchange as Binance.com, are more likely to be seen as a commodity or an asset. When adopting these theories a distinction between commodity-like and currency-like cryptocurrencies can be made. However, developers decide what technical characteristics a cryptocurrency gets (as described in paragraph 2.1.1). Resulting in developers determining how cryptocurrencies can be used eventually. Knowing this, it seems more useful to distinguish based on developers visions. Besides, this approach has another advantage, current volatility, described by Ciaian, et al. (2016), can be neglected as this approach is based on a holistic purpose rather than the current situation. When adopting this definition a distinction can be made among the currencies, see table 2.2.

Table 2.2: overview distinction cryptocurrencies based upon purpose. Retrieved from multiple online sources.

Commodity-like	**Application**	**Currency-like**	**Application**
Ethereum	Smart contracts (Ethereum Foundation, 2018)	Bitcoin	Decentralized payments (Nakamoto, 2008)
NEM	Administration application, secondary payments (NEM.io Foundation ltd, 2018)	Ripple	Quick and international payments (Ripple Labs, 2017)
		Litecoin	Decentralized payments (Litecoin Foundation, 2017)

Nonetheless, authors cannot find common ground whether cryptocurrencies are commodities, currencies or assets. Wang and Vergne (2017, p. 14) state: “*Strictly speaking, this study shows that cryptocurrency is neither currency nor commodity*”. They state, based upon empirical evidence, that cryptocurrencies can improve their technology, which is correlated with an increase of its price. Ordinary commodities (such as gold) are not able to continuously innovate. Therefore Wang and Vergne (2017) claim to embrace ‘synthetic commodity money’, which has characteristics of both a currency and commodity, but can still be improved. However, Hong (2017) and Blau (2018) see cryptocurrencies rather as an asset for investment. “*Bitcoin functions more as a speculative asset than as a traditional medium of exchange*” (Blau, 2018, p. 16). Hong (2017) on the other side shows that Bitcoin could be a valuable addition to a traditional portfolio: “*Bitcoin can be a good non-correlated alternative asset with high expected return that can be included in such portfolios*” (Hong, 2017, p. 271). Investors might decide to invest in cryptocurrencies not only for their high returns and non-correlarity, but also for the idea and technology behind it. This is in line with Wang and Vergne’s statement regarding the endless innovation possibilities of cryptocurrencies. To conclude, a distinction can be made based on nature, but this does not fully describe current influences and is based on a holistic view. Defining cryptocurrencies as assets seems therefore most applicable seeing the literature that supports at least Bitcoin as an alternative investment vehicle. Thus, for the purpose of this research, cryptocurrencies will be defined as assets containing a certain nature (either a commodity-like nature or currency-like nature, depending on which currency is studied).

3 THEORETICAL FRAMEWORK

Pricing theories help to understand differences in price, for example for firms, assets or commodities. However, previous research says little about a suitable valuation theory for cryptocurrencies. Hence, several valuation/pricing theories (purchasing power parity, cost-based, market demand and discounted cash flows) are defined and elaborated upon in order to select the most applicable theory for cryptocurrencies.

Different search queries are used compared to those used in the introduction. Appendix 6.2 contains an overview of the literature used in this chapter. Articles of all years are used to elaborate valuation theories in order to find the most applicable theory. Simply because some theories originated not in recent years, but are still commonly accepted nowadays. Therefore the selection of articles is based on relevance and impact (cited by). Besides, two relevant subject areas have been selected in Scopus to retrieve solely economic and financial papers (ECON and BUSI). Additionally, prescribed literature for the course Business Administration – Financial Management and books accessible via the University of Twente library have been used to clarify some theoretical concepts.

3.1 PURCHASING POWER PARITY

The Purchasing Power Parity theory (PPP) relates to valuing currencies and can be derived from the exchange rate and the purchasing power of two countries with different currencies. Bahmani-Oskooee (1993) states that the PPP, in its absolute form, is determined by the ratio of domestic and foreign price levels: "*the exchange rate between two currencies is determined by the national prices*" (Bahmani-Oskooee, 1993, p. 1023). Rogoff (1996) builds upon this theory and suggests that the PPP relies on a single rule: "*once converted to a common currency, national price levels should be equal*" (Rogoff, 1996, p. 647). In other words, once €1,000 is exchanged into sterling, someone should be able to buy similar items (similar purchasing power) in that specific country. Bahmani-Oskooee (1993) denotes the PPP as two equations displayed below. Equation one shows that the PPP theory suggests that the exchange rate between two currencies (R_{ij}) is determined by the relative price levels of both countries (P_i and P_j). Equation one can be rewritten into a second equation to clarify that currency i can be obtained by multiplying currency j with the exchange rate (R_{ij}).

$$(1) \quad R_{ij} = \frac{P_i}{P_j} \qquad\qquad (2) \quad P_i = R_{ij} * P_j$$

Taylor and Taylor (2004) recognize the definition by Rogoff (1996) and Bahmani-Oskooee (1993) regarding PPP. Additionally Taylor and Taylor (2004) specify two types of PPP: *absolute* PPP and *relative* PPP. Initially, there is absolute PPP if the purchasing power of two currencies are exactly equal once converted at the market exchange rate. This is rarely seen as it as it is difficult to control whether literally the same items can be purchased in different countries. Hence, the relative PPP is more common to use. This type of PPP relies upon the relative change in the inflation in the countries compared over the same period, this can also be written as equation three. Where R_{ij0} represents the exchange rate at the start of the time period and R_{ij1} represents the exchange rate after one year. I_j and I_i represent the inflation of both countries. Whenever the relative change of the exchange rate is similar to the difference in inflation the relative PPP holds. It is important to mention that when the absolute PPP holds, then the relative PPP also does. However, if the relative PPP holds, then the absolute PPP does not hold necessarily.

$$(3) \quad \frac{R_{ij_1}}{R_{ij_0}} = \frac{1 + I_j}{1 + I_i}$$

"*While few empirically literate economists take PPP seriously as a short-term proposition, most instinctively believe in some variant of purchasing power parity as an anchor for long-run real exchange rates*" (Rogoff, 1996, p. 647). Multiple authors recognize the fact that the relative PPP does not hold on the short-run but does hold on the long-run (Bahmani-Oskooee, 1993; Hoque, 1995; Rogoff, 1996; Taylor & Taylor, 2004). The explanatory power on the long-run is often examined by testing whether two price levels are cointegrated. This technique evaluates two individual time series in order to find or exclude a long-run relationship. Hence, if this relationship is balanced by the exchange rate, there is an equilibrium and the (relative) PPP holds. Nevertheless, the variables (price differences in this case) may drift apart in the short-run (Bahmani-Oskooee, 1993; Hoque, 1995). Regardless of the short-run inadequacy, the PPP provides a high explanatory power. Depending on the country and time period, high R squares can be recognized when using the cointegration technique. For instance, both Bahmani-Oskooee (1993) and Hoque (1995) did research towards the applicability to less developed countries. Bahmani-Oskooee found out that Ethiopia has an R squared of 0.85 between 1973 and 1988, while Argentina, Cameroon and Brazil had a R squared of 0.99 in the same time period. Whilst different values are recognized during the period between 1961 and 1990 by Hoque.

Recently Aoki (2013) tried to explain the deviation from the law of PPP due to the ongoing debate regarding the explanatory power of the PPP described by, among others, Taylor and Taylor (2004). Aoki (2013) created a model that takes into account several influential factors, including; wage rate, consumer price index, nominal interest rate, exchange rate per US dollar and money supply (per-population). The explanatory power of this model is tested on both developed as well as developing countries. Interestingly, these influencer have more explanatory power for developed countries given the higher R squared values. Whereas the R squared values of developed countries range between 0.4181 and 0.6757, while the R squared values of the developing countries are not higher than 0.3688.

3.1.1 Application to cryptocurrency

Little is written about the applicability of the PPP model on cryptocurrency. Hence, background information and theory regarding PPP are evaluated by the researcher and the applicability is assessed based on reasoning. Due to their decentralized design, cryptocurrencies are not influenced by some essential factors that underlie ‘ordinary’ currencies, such as the Dollar or Pound. For instance cryptocurrencies are not connected to a country specific purchasing power, inflation or price level. Moreover most cryptocurrencies have a relative short existence. The PPP model on the other hand is based upon these country specific factors and solely maintains a high explanatory power when used to explain long term differences in currency exchanges (Bahmani-Oskooee, 1993; Hoque, 1995; Rogoff, 1996; Taylor & Taylor, 2004). Furthermore, cryptocurrencies defined as assets rather than currencies. Thus, the PPP model is not applicable.

3.2 COST-BASED PRICING THEORY

The cost-based pricing theory, as its name inclines, determines the actual value based upon the cost price plus a profit margin/premium (Noble & Gruca, 1999; Kotler, Wong, Saunders, & Armstrong, 2005; Hinterhuber, 2016). Both Noble and Gruca (1999) and Kotler, et al. (2005) elaborate on the cost price further into variable costs and fixed costs. Both variable costs and fixed costs together determine the lower limit of prices. Equation four represents the cost-based pricing theory, where C_v represents variable costs, C_f represents fixed costs, p represents premium or desire profit margin and P represents the actual price. Nevertheless, equation four cannot explain the full extent of cost-based pricing due to several influential factors that have non-linear growth, such as economies of scale and economies of scope (Noble & Gruca, 1999; Franklin Jr. & Diallo, 2012).

$$(4) \quad C_v + C_f + p = P$$

The cost-based pricing theory usually relates to pricing products or services. Most authors speak about managers who determine if the cost-based pricing theory is adopted (Noble & Gruca, 1999; Hove, 2004; Kotler, et al., 2005; Franklin Jr. & Diallo, 2012; Hinterhuber, 2016). Besides, cost-based pricing is often mentioned among several product or service pricing models such as penetration pricing, leader pricing, parity pricing, price bundling and customer value pricing. Pricing strategies related/fairly similar to cost-based pricing are; rate-of-Return pricing, contribution pricing, contingency pricing, target return pricing and mark-up pricing. (Noble & Gruca, 1999; Kotler, et al., 2005; Hinterhuber, 2016). Hence, it can be assumed that cost-based pricing is often used or valuing products or services created by firms or authorities.

Despite the straight forward approach that results in a predictive profit margin some criticism regarding the cost-based pricing theory can be recognized. First of all, the cost-based pricing theory does not take into account competitive information (including demand) and consumer preferences (Noble & Gruca, 1999; Kotler, et al., 2005). Optimal profit margins vary among different type of customers. For example luxury products sold to high class consumers can be sold with a higher profit margin compared to budget products sold to lower class consumers. Cost-bases pricing seems therefore a logical solution when a manager has little or no information about the consumer, competition or demand. Noble and Gruca (1999) confirmed this thought with empirical evidence: "*The choice of cost-based pricing was positively and significantly related to the difficulty in estimating demand (p < 0.10). Firms in markets where demand is very difficult to estimate are almost 40% more likely to choose cost-based pricing than those in markets where demand is easy to estimate*" (Noble & Gruca, 1999, p. 451).

Secondly, cost-based pricing is not value maximizing, which results in lower profits. In a situation in which the average unit costs are likely to be consistent over time and at any point on the demand curve, cost-based pricing can be value maximizing. However, as stated before, due to economies of scope/scale that effects the linearity, none of these conditions are likely to hold very often (Noble & Gruca, 1999). For example, a firm needs a third machine to cope with the demand. However, the third machine is not working at full capacity while the others do. The firm still has to pay the purchasing value and for electricity. Resulting in higher average cost per product made, thus a higher selling price. Besides, Hove (2004) states that cost-based pricing is often inefficient and unfair. Hove suggest that it is inefficient due to distort decisions regarding certain services. Some products or services are distorted as they offer complementary free services, such as free travel or free maintenance. Free services are used more often just because their free, rather than due to their usefulness. This additional use causes distortions. Furthermore, Hove claims cost-based pricing to be unfair since certain costs of firms are not initiated by the product consumers are buying, but is simply charged to that product due to unmanageable factors such as information dispersion.

3.2.1 Application to cryptocurrency

Both Chatterjee, et al. (2017) and Hayes (2017) provide evidence of the cost structure of Bitcoin (Hayes also for altcoins). Chatterjee, et al. and Hayes conclude that the cost price of cryptocurrencies depend on two factors. The first factor is the reward for mining, which results in a negative correlation between the relative cost price of cryptocurrencies and the actual price. Mining (a vital part of the costs of cryptocurrencies) becomes more profitable when cryptocurrencies' prices are high. Miners receive a higher reward (in Dollars) for a mined block (the work they do). Thus, the costs for miners are proportionately less when the price of cryptocurrencies increase (Hayes, 2017).

Secondly, energy costs are part of the cost price of cryptocurrency. Electricity is a vital source to be able to create sufficient computing power to mine cryptocurrencies (Hayes, 2017). As described in paragraph 2.2, Litecoin and Dash offer quicker and less energy consuming payments compared to

Bitcoin (Nakamoto, 2008; Litecoin Foundation, 2017; The Dash Network, 2018). Hayes (2017) showed differences among cost-prices and energy consumption determine to some extent the carbon footprint of the cryptocurrencies. Nevertheless, Hayes did not discuss the influence of the costs on their pricing but he suggests that further research can reveal whether or not the carbon footprint of cryptocurrencies can be reduced. This rather technical field of research is outside the scope of this paper.

Nevertheless, when combining the findings of Hayes (2017) and Chatterjee, et al. (2017) with the theory of Noble & Gruca (1999), Kotler, et al. (2005) and Hinterhuber (2016), the cost price can be calculated by the energy costs for mining a single block plus an unknown premium. Hayes (2017) used this approach to simulate the cost price of cryptocurrencies. However, he stated that it is difficult to determine the cost price precisely, since mainly depend on the cost of electricity of miners. It seems impossible to determine electricity costs, because electricity prices differ across the world and it is impossible to locate every miner. Despite the fact that locations of mining pools are known, little can be said about the actual miner, as the mining pool's location solely indicates where its servers are located (BuyBitcoinWorldwide, 2018). Nevertheless, global energy prices differ, Hayes (2017) recognized this problem, but choose not to address it. The approach of Hayes (2017) is used in this research (see chapter 4), since the approach of Hayes (2017) corresponds well to previous theories. Contrary to Hayes (2017), global prices are used to address the miner location issue.

3.3 SUPPLY AND DEMAND THEORY

The supply and demand theory refers to a price derived from an intersect of two variables; supply and demand. Whereas 'supply' is represented by the stock or products available at the time and 'demand' is represented by the desired stock or products at the time (Marshall, 1890; Kotler, et al., 2005; Vali, 2014). Marshall (1890), supported by Cairnes and Mill (as cited in Marshall, 1890), combined the demand with multiple supply lines to visualize their relationship graphically, see figure 2.1. The demand curves (*DD'* and *dd'* in figure 2.1) show that price and demand are positively correlated, while quantity and demand are negatively correlated. Thus, a higher demand results in a high price, but in a lower quantity taken. Supply (*SS'* in figure 2.1) is subject to product characteristics. Fig. 24 shows an example of a price subject to regulations, while Fig. 26 shows a product that obtains its value from scarcity. Additionally Fig. 25 shows a 'normal' supply curve. Which is a slight convex since the costs of producing become relatively spoken less and/or the selling price increases.

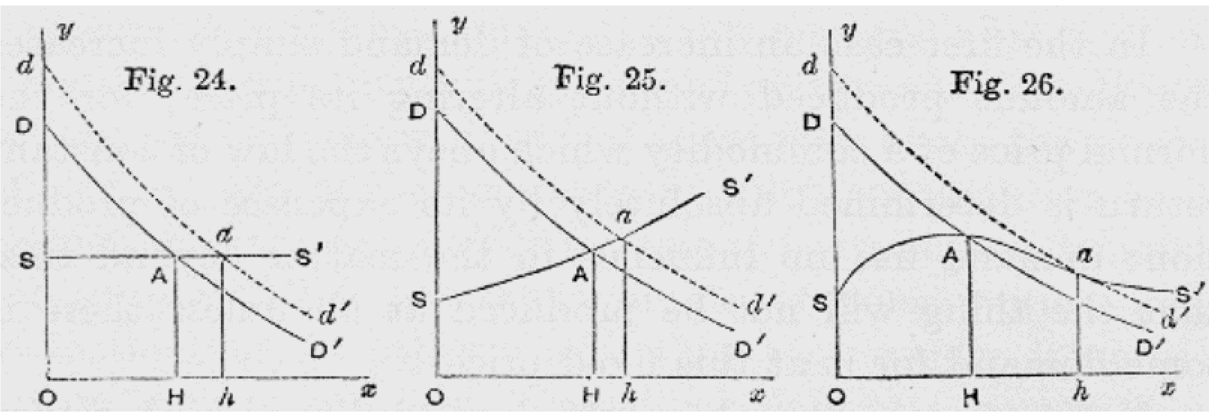

Figure 3.1: supply and demand graphs. Retrieved from Marshall (1890).

For example, when the demand is higher than the supply of products, firms usually increase production to cope with this increasing demand, profiting from economies of scale. However, if an industry cannot cope with the increase, firms might decide to increase prices in order to lower the demand for that product. In both cases the supply line grows more vertical. On the contrary, if the supply does not correspond well to the demand, firms can decide to lower their prices in order to sell excess stock, while the costs have already been made (Marshall, 1890; Kotler, et al., 2005). An equilibrium is reached once supply and demand are balanced again (*AH* and *ah* in figure 2.1). This 19th century' visualization is still commonly used among recent authors (Kotler, et al., 2005; Vali, 2014).

Simplified supply and demand curves can be written as a linear formula, such as equation five. Buyer's characteristics determine the value of *b* for the demand curve, for example (disposable) income. A rise of a buyer's income can cause line *DD'* to move to *dd'*. Multiple authors agree that the characteristics of buyers influence the demand curve (Marshall, 1890; Berry, Levinsohn, & Pakes, 1995; Vali, 2014). Whereas Berry, et al. (1995) speak of a level of utility, including both individual characteristics and product characteristics. Vali (2014) speaks about an 'behavioural equation', which explains changes of demand as a factor of price and disposable income. Both Luchansky and Monks (2009) and Vali (2014) define disposable income as increase of wages after inflation. The explanatory power of the model of Berry, et al. (1995) is high (R squared 0.66). Thus, 66% of the U.S. car prices can be explained by observable buyer characteristics (prices were log transformed to reduce skewness). Similarly the supply curve's *b* value is subject to supplier characteristics, such as production costs: "*Notable among these factors are the cost of production*" (Vali, 2014, p. 53). On the other hand, the slope (*a* value) of both supply and demand depends on their price elasticity. The equation of the price elasticity displayed in equation six has been used unaltered over the years in previous empirical research (Berry, et al., 1995; Luchansky & Monks, 2009; Dierker, et al., 2016). Whereas *Δx* represents the percent change in quantity and *Δy* represents the percent change in price.

$$(5) \qquad y = a\,x + b \qquad\qquad (6) \qquad b = \frac{\Delta\,x}{\Delta\,y}$$

Most theories described above relate to products or commodities, but currencies and assets can also be subject to supply and demand. Firstly currencies are subject to forces that bring them back to an equilibrium: "*the value of transactions would increase until people's demands for money were at such a level that they would be willing to hold the increased stock of money at this new high level of prices. Again there are forces bringing the demand for, and supply of, money back together*" (Kettell, 2002, p. 11). This pattern is similar to those of products displayed in figure 2.1 – Fig. 25. For instant, €1 is usually traded for $0.83. Person *a* needs dollars, but person *b* wants to holds his dollars. However, when person *a* offers 1.20 for 0.83, person *b* agrees due to the advantageous exchange price. The supply line still follows a slight convex line as a higher price results in relative lower cost price per unit. Secondly assets, multiple authors recognize the fact that assets, including stock prices, are impacted by supply and demand (Kraus & Stoll, 1972; Miyakawa & Watanabe, 2014). Additionally, Dierker, et al. (2016) state that fluctuating expectations can move investors from the sell-side to the buy-side, hence influencing the weight of elasticity.

Luchansky and Monks (2009) created a model including several factors that influence the demand and the supply. Their model has an explanatory power of 63.8% regarding the price of the commodity gasoline. Luchansky and Monks included four factors; substitutions (measured by corn prices), competition (or new or market entries, measured by number of gasoline firms), trends (measured by regulations and public opinion) and scarcity (measured by available gasoline per vehicle). These influential factors are defined in the section 3.3.1 till 3.3.4. Additionally the cost of carriage is explained.

3.3.1 Cost of carriage

Marshall (1890) states that the cost of carriage influences price, especially for heavy or large commodities. Marshall (1890) explains the cost of carriage by an example of bricks made in the south of the United Kingdom and sold in the North. Each town would use local bricks to pave roads and such.

Very special bricks (for instance due to hardness, colour or rarity) on the other hand will be sold more than 100 miles away from their quarry. This was due in 1890 however. Currently, due to globalization, the costs of transportation decreased. Menger, et al. (2007) agree with Marshall, but they increased the scale of the example: producing bricks in Brazil is cheaper than producing them in Germany. However, the German bricks are cheaper than Brazilian bricks to buy in Europe due to the cost a cargo ship that has to travel more than 6000 miles.

3.3.2 Substitutes and new market entries

Multiple authors agree that substitutes and new market entries ultimately cause a decrease in price (Berry, Levinsohn, & Pakes, 1995; Porter, 2008; Luchansky & Monks, 2009). For instance, Berry, et al. (1995) did research towards the price of automobiles. They suggest that a higher number of suppliers (new market entries) often results in a more diversified supply. Hence, buyers select the car they buy based upon characteristics such as maximum speed and quality of the interior. Berry, et al. (1995) showed that 66% of the price can be explained by observable characteristics (R2 0.66). They state that suppliers adjust their price (downwards) to stay competitive. For example, a lower maximum speed and quality results in a lower price. Luchansky and Monks (2009) at the other hand describe the influence of substitutes with an example of a substitute for gasoline, which is ethanol. They showed that during times of high oil prices (resource for gasoline) and low corn prices (resource for ethanol) the demand shifted from gasoline to ethanol. To prevent bankruptcy, gasoline producers lowered their price to stay competitive. Porter (2008) concludes that if the number of substitutes and new market entries are high, no company earns attractive returns on investment.

3.3.3 Trends

Kraus and Stoll (1972) state that the stock market is primarily subject to supply and demand. However, they recognize that the external factors public interest and trends influence supply and demand. such as external costs, macro-economic factors and public interest. First of all, Kraus and Stoll (1972), supported by Luchansky and Monks (2009), state that trends are of significance. Nevertheless, trends are an ambiguous phenomena to measure. Luchansky and Monks (2009) therefore focussed on a trend caused/forced by governmental regulations. They showed that regulations regarding gasoline and oil had a negative impact on the price of gasoline. Additional methods to measure trends, such as a (national) survey or media attention can reveal answers regarding some ambiguous trends.

3.3.4 Scarcity

Scarcity refers to the available of a certain good, when there is little available it is referred to as scarce. As described in paragraph 2.3 a certain extent of scarcity (thus limited available and not possible to copy) is a necessary good to maintain the value of a currency. Nevertheless, excess scarcity can raise prices and cause shifts among buyers and sellers. First of all, both Marshall (1890) and Kettell (2002) recognize that prices increase when scarcity exists. Product-wise, scarcity allows producers to increase prices, so they are able to earn a similar amount while selling less quantity. Dierker, et al. (2016) builds upon this theory and claims that scarcity can lead to substantial differences in price that persuades buyers to become sellers and vice versa.

3.3.5 Application to cryptocurrency

The supply and market theory seems applicable due to fact that cryptocurrencies can be freely traded and are influenced by scarcity. Previous research regarding price formation is limited to Bitcoin and does not have a clear consensus, but multiple authors agree (as is explained below) that cryptocurrency are subject to the forces of market and demand. First of all, since cryptocurrencies are defined as assets (with certain characteristics, commodity or currency, see paragraph 2.3), Hong (2017) and Blau (2018) point out that cryptocurrencies are substitutes for traditional investment opportunities such as stocks and obligations. Nevertheless, nothing is said about what new market entries for cryptocurrencies exactly are. Besides the number of new entries and substitutes, the characteristics of cryptocurrencies might also be able to explain value as is the case for other commodities (Luchansky & Monks, 2009). Cryptocurrencies with different purposes can also have a different value. Further research can reveal whether one cryptocurrency is superior to another. Moreover, if this superiority is correlated by reoccurring characteristics.

Secondly, most is written regarding trends. However, where Luchansky and Monks (2009) used regulatory changes and public opinion to define trends, most recent authors use search patterns or media attention (Ciaian, et al., 2016; Wang & Vergne, 2017). Nevertheless, multiple authors cannot find common ground regarding the effect of attention regarding the demand of Bitcoin. Both Ciaian, et al. (2016) and Wang and Vergne (2017) recognize an effect of attention regarding the value of Bitcoin. Whereas Ciaian, et al. measured market forces including trends such as public attention: "*Our empirical results confirm that market forces of BitCoin supply and demand have an important impact on BitCoin price*" (Ciaian, et al., 2016, p. 1813). However, where Ciaian, et al. (2016) recognize a slightly positive effect, Wang and Vergne (2017) recognize a slightly negative effect. Recently no authors have questioned this conclusion, but there is not made a distinction among different cryptocurrencies. This leaves room for further research.

Thirdly, it is known that cryptocurrencies face a certain scarcity as described in paragraph 2.2. This is caused by the limited amount of coins available. Hence, if the demand exceeds the supply of cryptocurrencies, it is likely that this will influence the price as there is a maximum amount of tokens/coins available. The price will rise until a cryptocurrency owner in this case is willing to sell some cryptocurrency due to the attractive price. The sale and purchase of cryptocurrency with corresponding fluctuations happens until an equilibrium is reached (Kettell, 2002). However, as Dierker, et al. (2016) indicated, should a growing availability, thus less scarcity, decrease the overall price level. Hence, the growing number of coins should, theoretically, decrease scarcity thus price. However, Wang and Vergne (2017) proved the opposite is the case for cryptocurrencies.

Finally, both the cost of carriage (which is zero for cryptocurrencies as they can be transferred online) and the (potential) number of users will not be investigated. There is no accurate data regarding the potential number of users per cryptocurrency (Pakrou & Amir, 2016). Research towards it will probably result in a survey, as was the case for Pakrou and Amir (2016) when they investigated the user intention and potential user base of India. Nevertheless, this is not within the scope of this research. The number of (potential) users is seen as a topic for future research.

Thus, the model of Luchansky and Monks (2009) seems applicable to cryptocurrencies since the model concerns commodities and this research concerns commodity-like assets. Furthermore, the variables used in the model of Luchansky and Monks (2009) are used before by multiple authors in regards to cryptocurrencies (Ciaian, et al., 2016; Wang & Vergne, 2017).

3.4 DISCOUNTED CASH FLOW METHOD

The discounted cash flow method (DCF) can be used to calculate the price of a firm upon its projected future cash flows. Besides firm valuation, DCF can be used to value assets or investments: "*discounted cash flow (DCF) techniques have been used to cope with the problems encountered by the deterministic or probabilistic evaluation of the investment alternatives*" (Karsak, 1998, p. 331). When valuing an asset, the returns are seen as cash flows. Multiple authors agree that value can be estimated based on future cash flows over an certain period, the exit or terminal value at the end of that period and a discount rate, which is represented by the perceived level of risk (Kaplan & Ruback, 1995; Hillier, Grinblatt, & Titman, 2012; French, 2013; Leach & Melicher, 2015). Additionally Armitage (2008) and Janiszewski (2011) appoint several financial determinants that are incorporated in the DCF, such as, taxes, dividends, disclosure costs and agency costs. The DCF is solely based on future free cash flows, these can be described as: "*cash flows that are available to all providers of the company's capital, both creditors and shareholders, after covering capital expenditures and working capital needs*" (Janiszewski, 2011, p. 88). The terminal value can be calculated by multiplying the projected cash flow for the final year by 1 + long-term growth rate (usually retrieved from market evidence) divided by the discount rate minus the long-term growth rate. This calculation is displayed in equation seven. Whereas *g* represents long-term growth rate, *r* represents the discount rate and CF_n the projected cash flow of the last year.

$$(7) \qquad Terminal\ value = CF_n * \frac{1+g}{r-g}$$

The cash flows of each forecasted year and the terminal value need to be added up to find the firm/asset value. However, both cash flows and terminal value need to be discounted first. The discount rate is composed of a risk free rate, a market risk rate and in some cases an asset/firm specific covenant (French, 2013). The weighted average cost of capital (WACC) is in some cases used for firm valuations (Armitage, 2008; Janiszewski, 2011; Hillier, et al., 2012). The cash flow value of each year needs to be divided by *1 + r* squared by the year. Hence, the influence of the discount rate increases every year. This increasing influence represents the growing risk and the money that could have been earned with a risk free investment. The terminal value discount rate is squared by the last year. Combining these findings, DCF can be written as equation eight. However, the calculation of DCF is best represented in a table, see table 2.3 for a five year example of DCF.

$$(8) \qquad DCF = \frac{CF_1}{(1+r)^1} + \frac{CF_2}{(1+r)^2} + \cdots + \frac{CF_n}{(1+r)^n}$$

Table 3.1: example discounted cash flow method (5% risk-free rate, 5% market risk and 10% long-term growth). Own creation of fictional company.

Year	Cash flow	Terminal value	Present value in %	Present value in €
1	€ 200,000		0.909	€ 181,800
2	€ 400,000		0.826	€ 330,400
3	€ 600,000		0.751	€ 450,600
4	€ 800,000		0.683	€ 546,400
5	€ 1,000,000	€ 21,000,000	0.621	€ 13,662,000
Market value				€ 15,171,200

Empirical evidence regarding DCF shows that this method has a high explanatory power. Kaplan and Ruback (1995) compared the explanatory power of multiple valuation methods, including three CAPM-based approaches and two forecast cash flow methods. They found out that all models have a high explanatory power regarding high leveraged transactions (HLTs): "*Our median estimates of discounted cash flows for 51 HLTs are within 10 percent of the market values*" (Kaplan & Ruback, 1995, p. 1091). Especially when the prices are log transformed high R squared values can be recognized (range between 0.95 and 0.97). Nevertheless, a small number of observations (n = 51) is used for this research. Results can therefore be biased. Responding to that, Lundholm and O'Keefe (2001) executed a research towards the difference and explanatory power of multiple valuation techniques. They reveal that no technique is superior to another. Differences are usually caused by flaws in the forecast: "*Research efforts in valuation would be better spent on the study of how to make more accurate forecasts of financial statement data, not in how to represent and discount the resulting flows of value*" (Lundholm & O'Keefe, 2001, p. 332). In other words 'rubbish in' means 'rubbish out'. However, the flexibility in forecasting makes it possible to use DCF valuation to present optimistic, pessimistic and realistic scenarios based on different set of assumption (Janiszewski, 2011).

3.4.1 Applicability to cryptocurrency

Little is written about the applicability of the DCF model on cryptocurrency. Hence, background information and theory regarding DCF are evaluated by the researcher and the applicability is assessed based on reasoning. The DCF seemed applicable at first. However, the quality its input cannot be guaranteed. The DCF can be used for assets and cryptocurrencies are defined as assets. Hence, the cryptocurrencies' returns must be used to predict cash flows. Besides, remaining required factors, such as long-term growth rate and risk rate, can be calculated based upon previous data (for example by calculating the mean/average growth and the standard deviation as showed by Hillier, et al. (2012)). Additionally a global risk free can be used. Despite the theoretical fit and possibilities to calculate factors, it is extremely difficult to predict cryptocurrencies returns due to the high volatility of cryptocurrencies. As indicated in the theory, 'rubbish in' is equal to 'rubbish out' (Lundholm & O'Keefe, 2001). Therefore the DCF valuation theory is not fully applicable.

3.5 TECHNICAL ANALYSIS

"*Technical, or chart, analysis of financial markets involves providing forecasts or trading advice on the basis of largely visual inspection of past prices, without regard to any underlying economic or 'fundamental' analysis*" (Taylor & Allen, 1992, p. 304). Blume, Easley and O'Hara (1994) agree with this definition and add that the information extracted from these data may reveal information regarding the fundamentals driving the return. Furthermore Neely, Weller and Dittmar (1997) suggest that technical analysis is primarily based upon the idea that prices move in trends which are determined by attitudes of investors: "*Since the technical approach is based on the theory that the price is a reflection of mass psychology ("the crowd") in action, it attempts to forecast future price movements on the assumption that crowd psychology moves between panic, fear, and pessimism on one hand and confidence, excessive optimism, and greed on the other.*" (Neely, Weller, & Dittmar, 1997, p. 406). Nevertheless, multiple authors agree that there is scepticism regarding technical analysis. Taylor and Allen (1992) and Blume, et al. (1994) claim that it is due to a lack of fundamental analysis. Therefore Taylor and Allen (1992) suggest to use both fundamental and technical analysis for the most exact estimates. Lo, Mamaysky and Wang (2000) claim that this scepticism is partially caused by linguistic barriers: "*technical analysis is primarily visual, whereas quantitative finance is primarily algebraic and numerical*" (Lo, et al., 2000, p. 1706). Furthermore, Neely, et al. (1997) provide empirical evidence that technical analysis can be profitable and contradict the scepticism. Park and Irwin (2007) reviewed 95 academic articles to address this issue of scattered acceptance and scepticism. They found out that 56 articles included positive results, 19 mixed results and 20 negative results. Additionally they distinguished among 'early' and 'modern' studies and 'domestic' (U.S.) and 'foreign' studies. Park and Irwin (2007) conclude that results of modern studies are more accurate due to an increased number of tested trading systems and more sophisticated bootstrap methods. Furthermore they state that 'modern' and 'foreign' reviews are more likely to be positive about technical analysis.

Multiple stock or asset prices over a various period of time provide the starting point of a technical analysis. These prices evolve in a nonlinear fashion over time. However, these nonlinearities contain certain patterns or regularities. Lo, et al. (2000) provide an equation to capture such regularities quantitatively, see equation 9. The price over time, P_t, can be calculated by an arbitrary fixed but unknown nonlinear function of a state variable X_t (denoted as $m(X_t)$) and with noise (ϵ_t). To be able to recognize patterns or regularities the function of *m(.)* should be smoothened. When function *m(.)* is smoothened, an average pattern can be recognized. This pattern can be used to estimate future prices. Various methods can be used to smoothen or average data. For example, orthogonal series expansion, projection pursuit, nearest-neighbour estimators, Kernel regression, average derivative estimators, splines, and neural networks (Lo, Mamaysky, & Wang, 2000; Park & Irwin, 2007).

$$(9) \qquad P_t = m(X_t) + \epsilon_t$$

Bettman, Sault and Schultz (2009) investigated the explanatory power of technical analysis. In their research, aimed to investigate whether technical and fundamental analysis are substitutes or complements, Bettman, et al. (2009) first tested how each technique performed in isolation. Their model for technical analysis showed high explanatory power as it showed a R squared of 0.7546. Bettman, et al. (2009) included return on equity ($price_{t+1}$ - $price_t$)/$price_t$) and prior prices ($price_{t\text{-six months}}$) as independent variables as is in line with theory of Taylor and Allen (1992) and Blume, et al. (1994). Additionally they included volume and scarcity in their model. The influence of volume is discussed in section 3.5.2 and 3.5.3. Additionally the bandwidth is explained.

3.5.1 Bandwidth

Lo, et al. (2000) show that adding an accurate bandwidth is crucial for the information explained by the function. They performed a Kernel regression to estimate the function of *m(.)*, see figure 3.2. If the bandwidth is too small (as is the case in the middle panel) the function is 'fitting the noise'. Various outliers (noise) distort the function line, which becomes useless as it cannot be extended for an estimation. Increasing the bandwidth too much on the other hand results in too much averaging, hence loss of information (right panel). When extending the function in the left panel, the trend is assumed to be decreasing. Loss of information usually results in moving towards the all-time trend, which does not have to be correct if, for example, a stock price gained new momentum due to a change in regulations. Thus, when using the correct bandwidth, the trend should continue. The left panel shows an accurate function due to an suitable bandwidth.

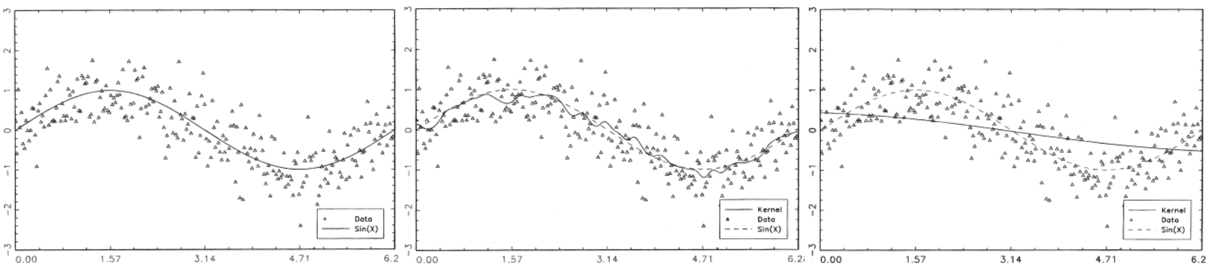

Figure 3.2: different functions caused by different bandwidths. Retrieved from Lo, et al. (2000).

3.5.2 Volume

Blume, et al. (1994) show that another factor, volume, has explanatory power regarding price. A low volume usually explains an unchanged or slightly changed price, while high volume explains a large positive or negative influence on the price. Consequently, Blume, et al. (1994), supported by Gallant, Rossi, and Tauchen (as cited in Blume, 1994) state that the slope of the relationship (sensitivity) is significantly affected by the availability and quality of information for investors. When there is little high quality information available the volume is more dispersed than when there is plenty high quality information available. When there is enough high quality available, the volume price relation would be 'V' shaped. Blume, et al. (1994) discovered this pattern by drawing 2,000 pairs of price and volume in three panels, see figure 3.3. The right panel shows a case where 10% of the data was available for the group of investors, the middle panel shows the results of a spread where 50% of data is available and the left panel shows the spread where 90% is available.

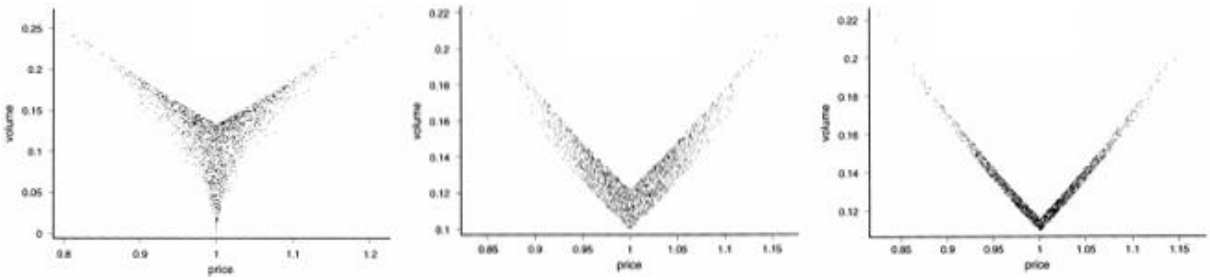

Figure 3.3: influence of quality information on volume and price. Retrieved from (Blume, et al., 1994).

The available information at t = 0 depends on the characteristic of the asset or stock. Nonetheless, both Blume, et al. (1994) and Park and Irwin (2007) recognize a common trend over time. They conclude that the available information for investors increases when a stock or asset matures. This increase in information is simply due to a longer period of time in which more observations (prices) are known and can be studied. Additionally, more fundamental information sources, such as annual reports can be distributed and studied.

3.5.3 Application to cryptocurrency

Little is written about the applicability of the technical analysis on cryptocurrency. Garcia and Schweitzer (2015) came closest to a technical analysis regarding cryptocurrency. They designed algorithmic trading strategies for Bitcoin. Resulting in in four strategies; 'Buy and Hold', 'Momentum', 'Up and Down' and 'Combined'. As parameters they have used obviously technical parameters such as volume and price. Additionally they added external 'social' or 'buzz' factors as is in line with Wang and Vergne (2017). These external factors can be seen as fundamental factors rather than technical factors. Nevertheless, the technical analysis factor 'volume' has been used by multiple authors to describe the price or returns of cryptocurrencies (Garcia & Schweitzer, 2015; Ciaian, et al., 2016; Wang & Vergne, 2017). Wang and Vergne (2017) state that a low liquidity, measured by volume, stimulates extreme prices. If someone wants to sell a bitcoin, but there are no buyers. The seller might insist on selling, hence he or she will lower the price until it is sold seller. This pattern is opposite for someone who is determined to buy. This statement contradicts the theory of Blume to the theory from (Blume, et al., 1994), who state that high volume is a sign of extreme prices. Volume and scarcity seem therefore applicable for further research. Prior prices on the other hand seem not applicable as there is no cause to believe that cryptocurrency is subject to seasonal influences. Whilst the model of Bettman, et al. (2009) includes multiple U.S. stock prices of firms that are possibly subject to seasonality. Hence, a model, based upon the model of Bettman, et al. (2009), including two explanatory factors (volume and scarcity) seems applicable.

3.6 HYPOTHESES

Four possible influential factors are derived from the theory, these are converted to hypotheses. All factors are derived from certain pricing theories. Hence, the hypotheses help to answer both sub questions. Some theories are not considered as they are not applicable. First of all, the PPP theory is not considered not to be applicable as described in paragraph 3.1.1. However, cryptocurrencies are measured in dollars at various websites. Furthermore, this research tries to explain the price of cryptocurrencies in dollars although the dollar is subject to country specific factors. Therefore parts of the PPP theory are considered as control variable but not used in this chapter to deduct a hypothesis.

Secondly, the cost-based pricing method seems not applicable at first sight. It seems unlikely that energy prices around the world increased by 3100% (as the cryptocurrencies did). Nevertheless, Hayes (2017) showed that there cryptocurrencies are subject to the influence of electricity costs.

Knowing this, hypothesis 1 is created to test the effects of the electricity prices on cryptocurrencies. Hypothesis 1 assumes that when energy prices increase (thus the costs), cryptocurrency prices increase too since the cost increase and the premium remains the same (see section 3.2).

Hypothesis 1: the price of cryptocurrencies is positively influenced by energy prices.

Thirdly, as indicated in paragraph 3.3.5 does the supply and demand theory apply to cryptocurrencies. Moreover, potential influential variables, such as substitutes and new market entries, external factors and scarcity have been evaluated and had explanatory power in previous research. Therefore hypotheses are created for all three influential factors. First of all, assuming cryptocurrencies are assets, in line with Hong (2017) and Blau (2018), substitutes can be recognized. To say, traditional and alternative investments as they are assets, but yield different characteristics. New currencies at the other hand can be seen as new market entries, since they yield similar characteristics and form competition. As described in the theory in paragraph 3.3.2 do both substitutes and new market entries have a negative influence on price levels, resulting in hypothesis 2a and 2b.

Hypothesis 2a: the price of cryptocurrencies is negatively influenced by new entries.
Hypothesis 2b: the price of cryptocurrencies is negatively influenced by substitutes.

Furthermore, trends and regulatory effects have been evaluated. Multiple researchers have written about this subject (Ciaian, Rajcaniova, & Kancs, 2016; Wang & Vergne, 2017). Whilst there is a lack of consensus regarding the explanatory power of attention, all authors agree that there is an influence of attention. This is in line with the theory. Hence, three hypotheses are created. Trends can be seen as positive, for example due to growing amount of usage, but also negative, for example due to hacks or fraud. Additionally, cryptocurrencies are not regulated, which is in line with their original protocol. Nevertheless, there are rumours about the regulation of cryptocurrencies, as this contradicts the very foundation of cryptocurrencies, this is seen as something negative. Hence, hypothesis 3a (total attention), 3b (regulatory related attention) and 3c (negative attention) are formulated.

Hypothesis 3a: the price of cryptocurrencies is influenced by attention.
Hypothesis 3b: the price of cryptocurrencies is negatively influenced by regulatory related attention.
Hypothesis 3c: the price of cryptocurrencies is negatively influenced by negative attention.

Another combination of theories can be found when evaluating theories regarding scarcity and technical analysis side by side. Technical analysis takes into account all available technical characteristics, including price and volume. Nevertheless, the circulating supply, hence scarcity, is also a technical characteristic so it should be able to explain price. Besides, as per theory (Dierker, Kim, Lee, & Morck, 2016), scarcity often results in higher prices. To test its influence hypothesis 4a is created. Furthermore the volume is considered as a technical variable. As described in paragraph 3.5.3 are the theoretical literature and the research towards cryptocurrency contradicting. Therefore hypothesis 4b is created to address this subject.

Hypothesis 4a: the price of cryptocurrencies is influenced by volume.
Hypothesis 4b: the price of cryptocurrencies is positively influenced by scarcity.

4 METHODOLOGY

To provide an answer to the research question a time series research design, containing multiple regression analysis, seems most suitable for this research. First of all, the aim of this research, explain the price formation, is in line with the purpose of time series analysis: "*The purpose of time series analysis is generally twofold: to understand or model the stochastic mechanism that gives rise to an observed series and to predict or forecast the future values of a series based on the history of that series and, possibly, other related series or factors*" (Cryer & Chan, 2008, p. 14). Secondly, a time series research design is a quantitative design, which makes the observation of high numbers of observations possible (Saunders, et al., 2015). Lastly, the decision of previous authors (Cheung, et al, 2015; Wang & Vergne, 2017; Blau, 2018) to use time series analysis is supported by Chatfield (2003), who states that time series analysis is an excellent choice for financial and economic research. Wang and Vergne (2017) used a weighted average of the prices of five cryptocurrencies and made statements regarding cryptocurrencies as a whole. Hayes (2017) on the other hand estimated a least squares multiple regression using cross sectional data in order to explain differences among cryptocurrencies. Similar to Wang and Vergne (2017) multiple regression analysis will be performed to explain price movements. Contrary to Wang and Vergne multiple separate regressions will be performed to be able to identify differences among cryptocurrencies. Additionally an overall weekly regression analysis, as seen in Wang and Vergne (2017), will be performed as this provides less noisy data and allows me to benchmark certain variables.

Figure 4.1 shows a schematic overview of the model and represents a summary of this chapter. The model can be subdivided into three models adopted from theories described in chapter three with high explanatory power. First of all, the cost-based pricing model is adopted from multiple sources (see section 3.2.1) who explain that this type of pricing consists of a cost price plus a premium. Secondly, the supply and demand model is adopted from Luchansky and Monks (2009), due to its applicability to commodities and the fact that is its variables are used before in regards to cryptocurrency (see section 3.3.5). The model of Luchansky and Monks (2009) had an adjusted R squared of 0.638. Thirdly, the technical analysis model is based upon the model of Bettman, et al. (2009). Two variables of their model are adopted as they seem applicable (see section 3.5.3) Their model was able to explain 75.5% of price movements. Additionally control variables are added, these are described in section 4.2.2. When combining all models a corresponding formula (below) is created, it includes two dimensions, where 'i' indicates the cross-section dimension (currency) and 't' indicates the time dimension (date).

$$\textit{Price crypto}_{it} = \beta_0 + \beta_1 \textit{*Supply \& Demand}_{it} + \beta_2 \textit{*Cost-Based}_{it} + \beta_3 \textit{*Technical Analysis}_{it} + \beta_4 \textit{*Control variables}_{it} + \varepsilon_{it}$$

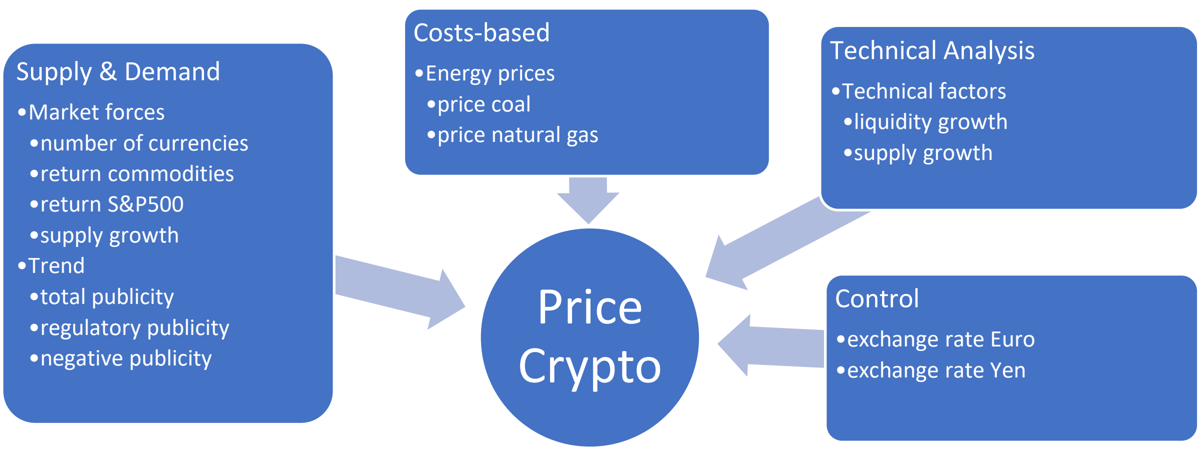

Figure 4.1: schematic overview time series panel data formula (own creation).

The remaining part of this chapter is structured as followed. First the selection and sample characteristics are described. An explanation regarding the variables and corresponding measurement instruments can be found in paragraph 4.2. The third paragraph includes an extensive review about the methods used and considerations made for collecting data. The final paragraph includes the methods, theoretical models and tests that are used to analyse the data. All additional literature is retrieved via University Twente's library (FindUT).

4.1 SELECTION AND SAMPLE

Both Green (1991) and Henseler (2017) claim that to maintain a statistical power of 0.8 the ratio observations to variables should be, at least 1 to 5, preferably 1 to 20. So, a minimum of 50 observations is required given the fact that there are 10 variables that can be tested simultaneously (see paragraph 4.2 and 4.4). Nevertheless, 200 observations are preferred, resulting in a total of 400 observations required to be able to test three models (see section 4.4) while maintaining a statistical power of 0.8. This cannot be accomplished by obtaining daily data, as proposed by Wang and Vergne. By doing this for five cryptocurrencies, they obtained 255 observations. Nevertheless, Wang and Vergne accumulated all observations and performed individual regressions. For the purpose of this research both separate and one averaged regressions are used (see section 4.4). Therefore daily observations are used when possible, if not possible weekly observations are used. Saturdays, Sundays and holidays (such as Christmas, Boxing Day, 4th of July) are excluded due to a lack of available data due to closed exchanges, an overview of excluded days can be found in appendix 9.4. Monthly data is avoided, because if data is retrieved once a month, four years of data is required to maintain statistical power of 0.8. Which results in only six coins that would be suitable for research of which only two are in the current top 100. Observing daily on the other hand allows to limit this research to a timespan of two years (when testing multiple models). Which allows to include the full length of the cryptocurrencies' rise (starting at 01-01-2017, see appendix 9.3) and similar time before.

The five largest cryptocurrencies, based on impact and age, are selected. The impact is measured according to the market capitalization as in line with Hayes (2017) and Wang and Vergne (2017). For this research the market capitalization is observed on December 31, 2017. A minimum age of two years is required to be able to test multiple years. Using both selection criteria the following cryptocurrencies can be, thus are, included in the sample; Bitcoin, Ripple, Ethereum, Litecoin and NEM. This sample covers 68.7% of the total market capitalization and represents 49.0% of the altcoins market capitalization, see figure 4.2. Nevertheless, these 5 cryptocurrencies are merely 0.37% of the total amount (1335 on December 31, 2017). By including multiple currencies, instead of solely Bitcoin, does this report distinguish itself from researches done by Böhme, et al. (2015), Ciaian, et al. (2016), Hong (2017) and Blau (2018).

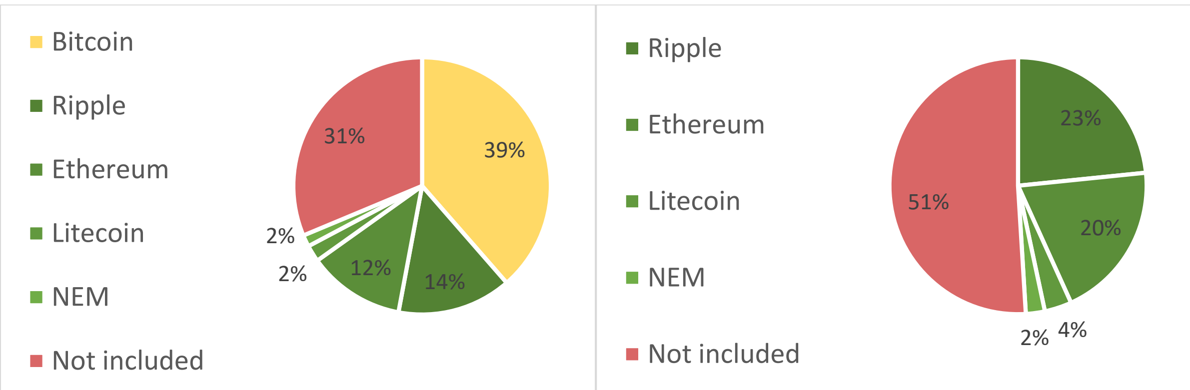

Figure 4.2: overview market cap (absolute and percentage) of total population and included sample. Left an overview of all cryptocurrencies and right an overview of all altcoins. Retrieved from Coinmarketcap.com (2017).

Table 4.1 shows an overview of some key characteristics of each included cryptocurrency. Bitcoin and Litecoin are the oldest cryptocurrencies. Both showed a lower annual return compared to the newer cryptocurrencies. Possible indicating that Bitcoin and Litecoin are more mature than the remaining three currencies. Ripple on the other hand experienced the highest annual return in 2017 despite the fact that it is an older cryptocurrency than Ethereum and NEM. Ethereum is the youngest cryptocurrency.

Table 4.1: key characteristics included cryptocurrencies. Retrieved from Coinmarketcap.com (2017) and section 2.2 and 2.3.

	AGE (01- 2017)	HIGHEST PRICE	GROWTH 2016	GROWTH 2017	BLOCKCHAIN AUTHORITY	BLOCK TIME	NATURE
BITCOIN	8.2 years	$ 19,768.40	122%	1435%	Decentralized	Heavy	Currency
RIPPLE	4.5 years	$ 3.41	9%	35048%	Partially decentralized	Light	Currency
ETHEREUM	2.4 years	$ 1369.78	747%	9571%	Decentralized	Light	Commodity
LITECOIN	5.3 years	$ 368.04	24%	5348%	Decentralized	Medium	Currency
NEM	2.3 years	$ 1.95	2177%	29173%	Partially decentralized	Light	Commodity

4.2 MEASUREMENT

The created measurement instruments of the variables are described in this paragraph. First of all the dependent variables are discussed. Secondly the independent and control variables are discussed in a corresponding section. Each section of variables includes the descriptive statistics of the corresponding variables. Table 4.2 contains an overview of all variables and summarizes this paragraph. A summary of the statistics and correlations can be found in section 4.4.2 (after corrective measures).

Table 4.2: overview measurement of the all the variables. Includes summary of measurement instrument and leading source(s) (between parentheses) in the second column. The third column shows in what model the variable represents a factor (also includes leading source between parentheses).

Dependent variables		
Name variable	**Measurement instrument**	
daily return cryptocurrency$_i$	$daily\ return_{\ i} = \frac{price_{i\ t+1} - price_{i\ t}}{price_{\ i\ t}}$ Formula based upon theory of Ciaian et al. (2016) and Wang and Vergne (2017).	
weekly return cryptocurrency	$weekly\ return\ cryptocurrency = \frac{\sum \frac{price\ cryptocurrency_{i\ t+7} - cryptocurrency_{i\ t}}{cryptocurrency_{i\ t}}}{n = i}$ Formula based upon theory of Wang and Vergne (2017), but relies on the unweighted average rather than weighted average.	
Independent variables		
Name variable	**Measurement instrument**	**Represented aspect**
number of currencies	Total number of currencies retrieved from the two distinguished online sources on Wednesdays (see section 4.3) (Luchansky & Monks, 2009)	New entries Supply and demand model (Luchansky & Monks, 2009)
daily return U.S. commodity index	$daily\ return\ commodities = \frac{price\ commodities_{t+1} - price\ commodities_{t}}{price\ commodities_{\ t}}$ Measured in U.S. dollars (Hong, 2017; Blau, 2018)	Substitutes Supply and demand model (Luchansky & Monks, 2009)

daily return SP500	$daily\ return\ S\&P500 = \frac{price\ S\&P500_{t+1} - price\ S\&P500_t}{price\ S\&P500\ _t}$ Measured in U.S. dollars (Hong, 2017; Blau, 2018)	Substitutes Supply and demand model (Luchansky & Monks, 2009)
negative publicity	Weekly 0-100 scale retrieved from retrieved from online source (see section 4.3) regarding negative searches (Wang & Vergne, 2017)	Negative trend Supply and demand model (Luchansky & Monks, 2009)
regulatory publicity	Weekly 0-100 scale retrieved from retrieved from online source (see section 4.3) regarding negative searches (Wang & Vergne, 2017)	Regulatory related trend Supply and demand model (Luchansky & Monks, 2009)
public interest	Actual daily number of Wikipedia page visits (Ciaian, et al., 2016)	Total trend Supply and demand model (Luchansky & Monks, 2009)
supply growth	$supply\ growth\ _i = \frac{circulating\ supply_{i\ t+1} - circulating\ supply_{i\ t}}{circulating\ supply\ _{i\ t}}$ (Wang & Vergne, 2017)	Scarcity Supply and demand model (Luchansky & Monks, 2009) Technical analysis (Bettman, et al., 2009)
coal price	Actual coal price in U.S. dollars retrieved from two distinguished online sources (see section 4.3) (Ciaian, et al., 2016; Hayes, 2017)	Cost of mining Cost-based model (Noble & Gruca, 1999; Kotler, et al., 2005; Hinterhuber, 2016)
natural gas price	Actual natural gas in U.S. dollars price retrieved from two distinguished online source (see section 4.3) (Ciaian, et al., 2016; Hayes, 2017)	Cost of mining Cost-based model (Noble & Gruca, 1999; Kotler, et al., 2005; Hinterhuber, 2016)
liquidity growth	Percentage growth of accumulated volume of 143 exchanges per cryptocurrency $liquidity\ growth\ _i = \frac{trading\ volume_{i\ t+1} - trading\ volume_{i\ t}}{trading\ volume\ _{i\ t}}$ (Wang & Vergne, 2017)	Volume Technical analysis (Bettman, et al., 2009)
Control variables		
Name variable	**Measurement instrument**	**Adopted from**
exchange rate Euro	Exchange rate Dollar/Euro (Ciaian, et al., 2016)	Strength dollar (Ciaian, et al., 2016)
exchange rate Yen	Exchange rate Dollar/Yen (Ciaian, et al., 2016)	Strength dollar (Ciaian, et al., 2016)

4.2.1 Dependent variables

There are six dependent variables. The first five consist of the daily return of each individual cryptocurrency. Similar to Ciaian et al. (2016) daily measurements are used to maintain statistical power (see section 4.1). Nevertheless, the choice of Wang and Vergne (2017) to use return rather than actual prices is adopted to be able to judge all five cryptocurrencies based upon the same scale (in percentages). Hence, formula 10 is used to calculate daily return. Where ‘i’ indicates the cross-section dimension (the cryptocurrency, for example Bitcoin) and ‘t’ indicates the time dimension (in days).

$$(10) \quad daily\ return_{\,i} = \frac{price_{i\ t+1} - price_{i\ t}}{price_{\ i\ t}}$$

Additionally a sixth dependent variable, weekly return cryptocurrency, is created. This variable is similar to the dependent variable Wang and Vergne (2017) used in their research. They added the data of five included cryptocurrencies to single panel. Resulting in the average of five observations per week, see formula 11. This allowed Wang and Vergne (2017) to have five observations per week while reducing noisy or missing daily data. Nevertheless, a different approach compared to Wang and Vergne (2017) is used. They used a weighted average (based upon market capitalization). However, Wang and Vergne acknowledged that his method resulted in a great dominance of Bitcoin. Therefore I chose to address this problem by using the unweighted average to calculate this dependent variable.

$$(11) \quad weekly\ return\ cryptocurrency = \frac{1}{n}\sum_{i=n}^{n} \frac{price\ cryptocurrency_{i\ t+7} - cryptocurrency_{i\ t}}{cryptocurrency_{i\ t}}$$

4.2.2 Independent variables

Cost-based model

As shown by Hayes (2017), cryptocurrencies costs are subject to electricity prices, especially due to the operating (mining) efforts. Nevertheless, the actual location of miners is unknown, so contrary to Hayes (2017) global electricity prices are used instead of U.S. energy prices. Additionally, it is unknown what the resource of electricity is that has been used. Unfortunately, no reliable or costless source could be found to provide daily or weekly electricity data on a global scale. However, electricity prices are subject to the prices of their resources. Coal, natural gas and oil are world's largest sources for electricity (Statista, 2018). Oil is subject to multiple factors and purchasers (for example by the transportation sector and macroeconomic factors). Hence, following the example of both Ciaian, et al. (2016) and Hayes (2017), the prices of the remaining two resources are used as the cost-based related measurement instruments *coal price* and *natural gas price*.

Supply and demand model

As indicated in section 3.6, two hypotheses are created in regards to new entries and substitutes. Therefore three variables are created to measure these hypotheses. First of all, one variable called *number of currencies* is created to represent new market entries as seen in the model of Luchansky and Monks (2009). New market entries (see section 3.3.2) are similar products or services. Hence, new cryptocurrencies are an obvious measurement instrument. However, the total number of cryptocurrencies is taken as measurement instrument for this variable as too time costly to review how many currencies are new and how many currencies did disappear. Luchansky and Monks (2009) experienced a similar bottleneck and chose to use the total number of ethanol producers as independent variable. Hence, I use the total number o currencies to represent new market entries. Substitutes on the other hand require more explanation. Assuming that cryptocurrencies are assets that are used for investment purposes, then both traditional and alternative investments are seen as substitutes. In line with Hong (2017) and Blau (2018) the S&P500 is used to represent the traditional investment. Similarly commodities are often seen as alternative investment, therefore the United States Commodity Index is used to represent alternative investments. Both Hong (2017) and Blau (2018) measured the return of these measurement instruments rather than actual price. Resulting in the second and third independent variables *daily return S&P500* and *daily return U.S. commodity index*. Both values are calculated using the same method as is used for the dependent variable. For the purpose of this research it is assumed that a higher return of both indexes is similar to a higher demand.

The second type of measurement instruments within the supply and demand model aim to find or exclude correlated factors related to trends. Various approaches are recognized when measuring trends. Wang and Vergne (2017) speak about ‘buzz’ factors, including number of searches, news items and number of transactions. While Cheung, et al. (2015) include both transactions and search queries to measure trends. Ciaian, et al. (2016) and Karasik and Kuzmina (2015) separate transactions from search queries and suggest that search queries are a credible measurement instrument to measure public interest. This research aims to identify the influence of all distinguished factors separately. Thus, three measurement instruments are created to measure three variables. Two measurement instruments are represented by search queries, as is in line with Wang and Vergne (2017). The amount of negative publicity, *negative attention,* is measured by the number of Google search queries that contain negative word combinations, similar to Wang and Vergne (2017). A new measurement instrument is created for the amount of regulatory related publicity *regulatory attention*, again the number of Google search queries is used, this time containing regulatory related word combinations. Both search queries are displayed in table 4.3. The *public interest* regarding cryptocurrency is, as in line with Ciaian, et al. (2016) represented by number of views on Wikipedia.

Table 4.3: overview of search queries per trend related variable.

Variable	**Number of Google search queries**
negative publicity	Cryptocurrency fraud, cryptocurrency Ponzi, cryptocurrency scam, cryptocurrency theft.
regulatory publicity	Cryptocurrency rules, cryptocurrency laws, cryptocurrency government.
Variable	**Number of Wikipedia page views**
public interest	Bitcoin, Ripple (payment protocol), Ethereum, Litecoin, NEM

Lastly, multiple sources (Marshall, 1890; Kettel, 2002, Dierker, et al., 2016) claim that scarcity has an influence on supply and demand. Therefore I included this variable. This variables formula is described later in this section (technical analysis).

Technical analysis model

Three independent variables based upon technical analysis are created; *supply growth, volume* and *prior price*. First of all *supply growth* is created to measure scarcity. Theoretically, an increase of circulating coins or tokens (hence scarcity) should result in a lower price (Marshall, 1890; Kettell, 2002). Every transaction is associated with a mining reward, so every transaction results in a larger supply of coins/tokens. All cryptocurrencies differ highly in the number of circulating supply. To mitigate this issue and provide a better scale the *supply growth* is taken rather than actual circulating supply. The calculation can be found in formula 12.

$$(12) \qquad supply\ growth_{\ i} = \frac{circulating\ supply_{i\ t+1} - circulating\ supply_{i\ t}}{circulating\ supply_{\ i\ t}}$$

The trading volume of cryptocurrencies is the second independent variable based upon technical analysis. This variable is called *liquidity* similar to Wang and Vergne’s research and it includes the accumulated volume of 143 exchanges including major exchanges such as Kraken, Binance, Bitstamp and Bitfinex (CoinGecko, 2018). Again, I chose to denote this variable in growth percentages create a similar scale per cryptocurrency as can be seen in formula 13.

$$(13) \qquad liquidity\ growth_{\ i} = \frac{trading\ volume_{i\ t+1} - trading\ volume_{i\ t}}{trading\ volume_{\ i\ t}}$$

4.2.3 Control variables

Two control variables are included to mitigate the effect of the strength of the dollar. Cryptocurrencies' price is denoted in dollars. However, the Dollar is subject to its own volatility. A weak dollar would result in a higher price for cryptocurrencies, while this does not have to have an impact on, for example, European investors. Where Ciaian, et al. (2016) used a single control variable *exchange rate* (exchange rate USD/EUR), I choose to mitigate this effect the exchange rates of both an European and Asian currency. Resulting in the variables *exchange rate Euro* which represents the exchange rate in Euro and variable *exchange rate Yen* which represents the exchange rate in Yen.

4.3 DATA COLLECTION

Data regarding cryptocurrencies, such as *daily return cryptocurrency* and *supply growth* are retrieved from Coingecko.com and Coinmarketcap.com as is in line with Ciaian, et al. (2016) and Wang and Vergne (2017). Coingecko.com is used to retrieve, *daily return cryptocurrency*, *liquidity growth* and *supply growth*. Coingecko.com is used most often since it has the possibility to download 'CSV' files per currency. However, *number of currencies* is not available on Coingecko.com. Hence, these are retrieved from the weekly 'snapshots' available on Coinmarketcap.com. The data in these snapshots are compared with the data retrieved from Coingecko.com to ensure correctness, no inequalities have been detected.

Six websites are selected to retrieve data for 15 variables. First of all, financial data *coal price*, *natural gas price*, *daily return U.S. commodity index* and *daily return S&P500* are retrieved from Finance.yahoo.com and Investing.com. Both Yahoo! and Investing.com provide secondary data retrieved from, among others, S&P Global Market Intelligence, Morningstar, Inc, Thomson Reuters and associated stock exchanges (Yahoo!, 2018; Investing.com, 2018). Secondly, Trends.google.com, is used to retrieve values for represented by search queries. Whereas Ciaian, et al. (2016) used Wikipedia views, Wang and Vergne (2017) used Bing searches. However, I did not have access to Bing search statistics due to its costs. Wikipedia views on the other hand does not offer the possibility to complement cryptocurrency with important additions such as 'fraud' or 'regulations'. Trend.Google.com will therefore be used as an alternative to measure *negative attention* and *regulatory attention*. Nevertheless, Trend.google.com does solely provide weekly percentages, rather than actual searches. Wikipedia views are therefore seen as a more reliable measurement instrument to measure *public interest*, as is in line with Ciaian, et al. (2016).

Table 4.4: overview of data sources per measurement instrument.

Variable	Source	Limitations
daily return cryptocurrencies, supply growth, liquidity	Coingecko.com & Coinmarketcap.com	
number of currencies	Coinmarketcap.com	Only available on weekly basis
Daily return U.S. commodity index, daily return S&P500, exchange rate Euro, exchange rate Yen, price coal, price natural gas	Finance.yahoo.com Investing.com	
negative attention, regulatory attention	Trends.google.com	Provides percentages based on the period rather than actual values
public interest	Tools.wmflabs.org	

4.4 DATA ANALYSIS

The time series data is regressed using multiple linear or OLS regression as there is one metric dependent variable at a time and multiple metric independent variables. Regression analysis are suitable when a researcher can distinguish both endogenous (dependent) variables and exogenous (explanatory or independent) variables (Ostrom, 1990; Cryer & Chan, 2008). Additionally, Henseler (2017) states that regression analyses are the most suitable choice when the research includes solely metric observations. This research does only include metric observations. The endogenous variable, cryptocurrencies' price, is represented in an absolute price and the exogenous variables are (converted to) absolute, thus metric, values. Additionally, Ostrom (1990) distinguishes two types of regressions; non-lagged and lagged. A non-lagged model can be used to explain differences in time series because it captures the relationships of variables observed at the same point in time. A lagged model on the other hand can be used to predict differences in time series, since it describes the relationship between a dependent variable at time *n* and independent variables at time *n-1*.

All five cryptocurrencies are regressed individual to be able to assess individual characteristics. Daily data is required to test this (see section 4.3). However, results of daily data are, at least, noisy. Therefore another dataset is created using weekly data including the average of all cryptocurrency specific variables. Additionally, in line with previous research multiple panels will be used to be able to assess performance during different times with certain characteristics (Karasik & Kuzmina, 2015; Ciaian, Rajcaniova, & Kancs, 2016). Therefore, I split the sample period into 01-01-2016 until 31-12-2016 and 01-01-2017 until 31-12-2017. Which allows to observe differences between a 'normal' year (2016) and a year including a rapid increase in price (2017). The whole sample period is studied in a last panel (2016 and 2017). Lastly, as described in the introduction of this chapter, five models are tested in order to investigate differences among influential factors. Each model is created to test the a certain type of influential factor (supply and demand, cost-based). All five models are displayed in table 4.5.

Table 4.5: overview tested models.

Model	Primary influential force	Included variables
1	Supply and demand (Luchansky & Monks, 2009)	*number of currencies, daily return U.S. commodity index, daily return S&P500, public interest, regulatory attention, negative attention, supply growth*
2	Cost-based (Hayes, 2017)	*coal price, natural gas price*
3	Technical analysis (Bettman, et al., 2009)	*liquidity growth, supply growth, prior returns*
4	All factors	*number of currencies, daily return U.S. commodity index, daily return S&P500, public interest, regulatory publicity, coal price, natural gas price, liquidity, supply growth, prior returns*

4.4.1 Assumptions OLS multiple regression

To be able to perform any OLS regression four assumptions must be met (Montgomery, Peck, & Vining, 2001; Henseler, 2017). These assumptions and how these are tested are described below. All assumptions described were not met with the original 'raw' data set. Therefore a corrective measure are applied, these are elaborated upon in section 4.4.2.

Linearity of the phenomenon measured

The first assumption of OLS regression requires that the phenomena measured are linear. A non-linear pattern (or bowed) indicates non-linearity. Polynomial regression, non-linear regression or transforming data is required if the linearity assumption is not met (Montgomery, et al., 2001; Henseler, 2017). This assumption is tested by plotting the independent and dependent variables in a scatter plot (a scatter matrix with all possible testable combinations can be found in appendix 9.6). Both the non-transformed data and transformed data do not show a bowed pattern, which indicates that the phenomena measured are linear.

Normality of the residuals' distribution

The residuals, errors of the regression line, must by definition be distributed normally. This assumption is best tested by performing the regression analysis and create a histogram of the residuals, see appendix 9.5. The data before corrective measures shows presence of kurtosis indicates that the distribution is not fully normal (Montgomery, et al., 2001). The distribution in the histogram of the transformed data at the other hand seems normal, so the second assumption is met.

Constant variance of the residuals

The assumption of constant variance of the residuals or heteroscedasticity is tested by creating scatter plots using the standardized residuals at the Y-axis and the standardized predicted values at the X-axis, appendix 9.5. Whereas the untransformed data shows a strongly centralized starting point at the left side of the graph and widens when moving to the left right of the plot. Resulting in some kind of cone shaped pattern, which suggests there is homoscedasticity. The scatter plot of the transformed data at the other hand, shows a more rectangular shaped pattern. Which suggests heteroscedasticity, so this assumption is met.

Independence of the residuals

Residuals can be subject to autocorrelation. Which literally means coherence with itself. In other words, if autocorrelation occurs, successive residuals are not independent of each other. Therefore the Durbin Watson test is used to reveal possible autocorrelations. The Durbin Watson test is especially useful for time series analysis as the order is of importance for this calculation (Chatfield, 2003). By using this function an output value between 0 and 4 is given. As a rule of thumb, values between 1.5 to 2.5 are statistically insignificant, whilst <1.5 is positive auto correlated and >2.5 is negative auto correlated (Montgomery, Peck, & Vining, 2001). Additionally, a scatterplot containing time versus the residuals shows whether residuals are independent (scattered randomly) or autocorrelated (contain a trend).

4.4.2 Specification tests and corrective measures

Log transformation

Log transformation is used as corrective measure. Why log transformation is used is best described by Olive (2017, p. 37): "*Theory, if available, should be used to select a transformation. Frequently, more than one transformation will work*". Montgomery et al. (2001) agree with Olive. Hence, similar to previous research by Wang and Vergne (2017) a natural log transformation is performed. Both *daily return cryptocurrencies* and *public interest* are logged, as is in line with Wang and Vergne. Prior to the log transformation a constant value of +1 is added since not all values are 0 or higher. Which is also adopted from previous research by Wang and Vergne (2017). Adding +1 as a constant does not influence the outcomes produced by the natural logarithmic transformation (Olive, 2017). In all cases, a natural log is performed since this yields directly interpretable proportional differences and is therefore most commonly used in the field of finance and economics (Gelman & Hilll, 2017).

Winsorization

In addition to the natural log transformation some corrective measures are applied regarding outliers. Normally outliers should be handled depending on its characteristics (Montgomery, Peck, & Vining, 2001; Henseler, 2017):

- The outlier is the result of an error occurred in the observations or data entry. Remedy: delete the case or correct the data.
- An observation is valid (thus explainable by an extraordinary situation) but exceptional (thus differs extremely from other observations). Remedy: delete the case or include variables that reflect this extraordinary situation.
- An exceptional observation with no likely explanation. Remedy: both deleting or inclusion cannot be justified. Hence, analyses with and without the outlying observations must be performed in order to assess the differences.
- An overall exceptional observation, but ordinary in its individual characteristics. Remedy: no changes should be made.

The second description reflects the characteristics of this dataset most accurate. The first description is met as there are no mistakes made in the observation nor the data entry. Secondly, the exceptional observations do have a likely explanation: cryptocurrencies are known for their volatility (Ciaian, et al., 2016). Hence high returns or high losses are explainable, so the third description is not met. Finally, the exceptionality of the observations was in all cases caused by one or two extra-ordinary (financial value) rather than by all individual characteristics, so the last description is not met.

Most outlying observations were caused by extraordinary high or low values of financial variables (*daily return cryptocurrencies*, *daily return U.S. commodity index, daily return S&P500, exchange rate Euro, exchange rate Yen, price coal, price natural gas*). Financial values, such as stock returns and return on assets, are often subject to extraordinary values (Adams, Hayunga, Mansi, & Reeb, 2017). Thus, the second description is most suitable, since the observations are extraordinary but explainable. Outlier mitigation methods are commonly used due to the normality of outliers within financial research. Adams, et al. (2017) showed that winsorization (49%), trimming (16%) or dropping (15%) observations are the most common measures to deal with outliers in the period between 2008 and 2012. Therefore winsorization is used to mitigate the outliers within the current data file. Winsorization can be defined as a technique that transforms (extreme) outliers to the closest 'normal', usually based upon a certain boundary percentage (Tukey, 1962). For this research the boundary percentage is 90%, resulting in winsorizing all data below 5th percentile and above 95th percentile.

Pearson correlation coefficient

Some variables are subject to multi collinearity. Knowing which variables are highly correlated allows me to use variables interchangeably or remove them from the model to simplify it. Montgomery, et al. (2001) state that the Pearson correlation test helps to assess whether multi collinearity is present. Gerber and Finn (2005) add that the Pearson correlation coefficient can be used to assess the strength of the association by the absolute value of correlation. Therefore the Pearson correlation coefficient can be used to remove or replace variables with a strong correlation. Gerber and Finn (2005, p. 69) state: "*As a rule of thumb, correlations between 0 and .30 (absolute value) are considered weak; those between .31 and .60 (absolute value) are considered moderate, and those greater than .60 (absolute value) are considered strong.*". Strongly correlated variables (see section 4.4.3) are not used simultaneously to reduce multi collinearity. The included variables are selected in such order that most of the original variables are included for each model. For example, when *number of currencies* is strongly correlated with both *supply growth* and *public interest*, but *supply growth* and *public interest* are not strongly correlated with each other. I withdraw *number of currencies* from the model instead of both *supply growth* and *public interest*.

Table 4.6: statistics daily data.

	2016				2017				2016-2017			
	Min.	**Max.**	**Mean**	**S.D.**	**Min.**	**Max.**	**Mean**	**S.D.**	**Min.**	**Max.**	**Mean**	**S.D.**
DAILY RETURN BITCOIN	-.068	.063	.002	.021	-.068	.063	.007	.037	-.068	.063	.005	.030
DAILY RETURN RIPPLE	-.068	.142	.001	.031	-.068	.142	.014	.060	-.068	.142	.008	.048
DAILY RETURN ETHEREUM	-.092	.138	.008	.057	-.092	.138	.014	.058	-.092	.138	.011	.058
DAILY RETURN LITECOIN	-.082	.099	.001	.026	-.082	.099	.006	.053	-.082	.099	.003	.042
DAILY RETURN NEM	-.106	.147	.004	.059	-.106	.147	.013	.069	-.106	.147	.008	.064
LIQUIDITY GROWTH BITCOIN	-.425	1.083	.052	.345	-.425	1.083	.165	.459	-.425	1.083	.108	.410
LIQUIDITY GROWTH RIPPLE	-.527	2.291	.214	.640	-.527	2.291	.334	.808	-.527	2.291	.274	.730
LIQUIDITY GROWTH ETHEREUM	-.572	1.971	.226	.730	-.572	1.971	.210	.647	-.572	1.971	.218	.689
LIQUIDITY GROWTH LITECOIN	-.492	1.568	.075	.459	-.492	1.568	.175	.603	-.492	1.568	.125	.538
LIQUIDITY GROWTH NEM	-.617	2.701	.298	.928	-.617	2.701	.206	.733	-.617	2.701	.252	.837
SUPPLY GROWTH BITCOIN	.000	.001	.000	.000	.000	.000	.000	.000	.000	.001	.000	.000
SUPPLY GROWTH RIPPLE	-.007	.012	.000	.002	-.007	.012	.000	.002	-.007	.012	.000	.002
SUPPLY GROWTH ETHEREUM	.000	.004	.001	.000	.000	.002	.000	.000	.000	.004	.000	.000
SUPPLY GROWTH LITECOIN	.000	.001	.000	.000	.000	.001	.000	.000	.000	.001	.000	.000
SUPPLY GROWTH NEM	0	0	0	0	0	0	0	0	0	0	0	0
NUMBER OF CURRENCIES	449	651	578.88	53.76	617	1334	915.73	212.02	449	1334	747.31	228.68
DAILY RETURN COMMODITY INDEX	-.010	.010	.000	.005	-.010	.010	.000	.005	-.010	.010	.000	.005
DAILY RETURN S&P500	-.010	.011	.000	.006	-.010	.011	.001	.004	-.010	.011	.001	.005
EXCHANGE RATE EURO	.867	.947	.903	.020	.841	.947	.887	.040	.841	.947	.895	.032
EXCHANGE RATE CHINESE YEN	6.490	6.913	6.644	.129	6.490	6.913	6.758	.129	6.490	6.913	6.701	.141
NATURAL GAS PRICE	1.900	3.393	2.552	.484	2.564	3.393	3.019	.177	1.900	3.393	2.785	.433
COAL PRICE	34.050	64.250	44.407	9.581	49.900	64.473	57.030	4.549	34.050	64.473	50.657	9.818
NEGATIVE ATTENTION	0	17	3.52	3.33	0	100	25.62	25.25	0	100	14.57	21.12
REGULATORY ATTENTION	0	10	1.13	2.54	0	100	23.81	28.37	0	100	12.47	23.10
PUBLIC INTEREST	9.120	11.428	9.458	0.227	9.576	12.869	10.634	0.714	9.120	12.869	10.046	0.791

Table 4.7: statistics weekly data.

	2016				2017				2016-2017			
	Min.	**Max.**	**Mean**	**S.D.**	**Min.**	**Max.**	**Mean**	**S.D.**	**Min.**	**Max.**	**Mean**	**S.D.**
WEEKLY RETURN CRYPTOCURRENCY	-.116	.287	.033	.087	-.116	.318	.085	.121	-.116	.318	.059	.108
WEEKLY LIQUIDITY GROWTH CRYPTOCURRENCY	-.771	1.763	.271	.597	-.771	1.763	.294	.660	-.771	1.763	.283	.627
WEEKLY SUPPLY GROWTH CRYPTOCURRENCY	.000	.004	.001	.001	-.001	.003	.001	.001	-.001	.004	.001	.001
NUMBER OF CURRENCIES	449	651	578.88	54.18	617	1334	915.73	213.68	449	1334	747.31	229.57
WEEKLY RETURN COMMODITY INDEX	-.021	.023	.000	.014	-.021	.023	.000	.007	-.021	.023	.000	.011
WEEKLY RETURN S&P500	-.021	.023	.003	.012	-.018	.023	.002	.008	-.021	.023	.002	.010
EXCHANGE RATE EURO	.871	.949	.903	.020	.842	.949	.887	.040	.842	.949	.895	.033
EXCHANGE RATE CHINESE YEN	6.493	6.919	6.644	.129	6.524	6.919	6.757	.131	6.493	6.919	6.701	.141
NATURAL GAS PRICE	1.900	3.393	2.541	.483	2.592	3.332	3.015	.174	1.900	3.393	2.778	.433
COAL PRICE	34.050	63.050	44.395	9.666	49.900	64.473	57.033	4.629	34.050	64.473	50.714	9.859
NEGATIVE ATTENTION	0	17	3.52	3.36	0	100	25.62	25.45	0	100	14.57	21.20
REGULATORY ATTENTION	0	10	1.13	2.56	0	100	23.81	28.59	0	100	12.47	23.19
PUBLIC INTEREST	9.245	10.039	9.450	0.165	9.624	12.619	10.658	0.739	9.245	12.619	10.054	0.808

Variance Inflation Factor

Another indicator for multi collinearity is the Variance Inflation Factor (VIF) according to both Montgomery, et al. (2001) and Gerber and Finn (2005). VIF values range from 1 upwards. Whereas a value of 1 indicates that the variable is not subject to multi collinearity, a value between 1 and 5 indicates that a variable is subject to moderate multi collinearity and a value higher than five indicates that a value is subject to high multi collinearity. Wang and Vergne (2017) also used VIF values to test for multi collinearity. Furthermore SPSS supports a function that deducts VIF values for each individual variable when running regression analysis. Hence, I VIF values for each variable are deducted and can be found in appendix 9.6. These values show that there are no correlated variables included in one of the models.

4.4.3 Descriptive statistics and correlations

Table 4.6 and 4.7 show an overview of the statistics for each variable. All variables in these tables are submitted to corrective measures (natural logarithm and winsorization). Three considerations can be made regarding the statistics. Furthermore the correlation matrices (table 4.8 and 4.9) are discussed.

First of all, the weekly values represented in table 4.7 can best be compared with previous research of Wang and Vergne (2017). They used similar corrective measures and data for weekly return. The statistics represented by Wang and Vergne are slightly more extreme/higher than the statistics of this dataset (2014-2015 versus 2016-2017). Wang and Vergne deducted the following statistics regarding weekly return; mean 0.17, standard deviation .1404, low -.42.22 and high .8931. Whereas I found; mean .0591, standard deviation .1078, low -.1158 and high .3182. Both standard deviations are similar and confirm the volatility of cryptocurrency compared to an ordinary stock such as the S&P500 (standard deviation .0103). Nevertheless, the largest decrease is almost four times smaller and the largest increase almost three times smaller. This is possibly indicating that (some of) the included cryptocurrencies move to a more mature stage with higher stability. Despite the similarities in with Wang and Vergne's research, different measurement instruments or data sources are used for variables such as negative attention (Bing search data versus Google Trends data and Wikipedia page visits). Nevertheless both *negative attention* and *regulatory attention* are adopted from trends.google.com and share a 0-100 scale as can be seen at the column for minimum and maximum values. It seems that *regulatory attention* is less present in 2016 due to its lower mean and standard deviation, and vice versa in 2017. Ciaian et al. (2016), who used a similar approach do not provide statistics in their final report.

Secondly, when looking to both weekly and daily statistics some different patterns can be recognized per year. The standard deviation (for weekly data) of non-cryptocurrency related variables, such as U.S. commodity index, S&P500 and coal price are lower in 2017 compared to 2016. Indicating that 2016 was a more volatile year when assessing it from a weekly perspective. The cryptocurrency related variables, such as return Bitcoin, attention total, number of currencies and liquidity growth Ripple show an opposite trend. Indicating that 2017 was a more volatile year. Additionally, all variables show higher means and often higher maximum values (the high and low values are often similar among both years, this is possibly caused by the winsorization I applied). This finding supports the assumption that 2017 was a year of extreme growth as can be seen in appendix 9.1. This trend of extremer and higher values for cryptocurrency related variables is still applicable when using daily data. The higher volatility of non-cryptocurrency related variables is more or less neglectable when assessing it from a daily perspective.

Lastly, due to the absence of the daily statistics of Ciaian, et al. (2016) it is difficult to benchmark most of the daily data. Furthermore, unscaled data, such as *exchange rate Euro*, *natural gas price* and *public interest,* is not discussed due to a lack of benchmarking possibilities. This is seen as one of the limitations of this report (see section 7.1).

*Table 4.8 (a): correlation matrix daily data set 2016. Significant values are denoted with * p<0.10. ** p<0.05. ***p<0.01. Strong correlations (0.60< or -0.60>) are written red.*
Legend: 1 daily return Bitcoin, 2 daily return Ripple, 3 daily return Ethereum, 4 daily return Litecoin, 5 daily return NEM, 6 liquidity growth Bitcoin, 7 liquidity growth Ripple, 8 liquidity growth Ethereum, 9 liquidity growth Litecoin, 10 liquidity growth NEM, 11 supply growth Bitcoin, 12 supply growth Ripple, 13 supply growth Ethereum, 14 supply growth Litecoin, 15 number of currencies, 16 daily return commodity index, 17 daily return S&P500, 18 exchange rate Euro, 19 exchange rate Chinese Yen, 20 natural gas price, 21 coal price, 22 negative attention, 23 regulatory attention, 24 public interest.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	1																							
2	.055	1																						
3	.000	.022	1																					
4	.774**	.064	.017	1																				
5	.354**	.161**	.139*	.289**	1																			
6	.075	-.093	-.019	-.009	-.055	1																		
7	-.053	.229**	-.039	.006	.042	.166**	1																	
8	-.051	-.114	.082	-.045	-.061	.120	.097	1																
9	.030	-.086	-.120	.072	-.165**	.512**	.126*	.186**	1															
10	.057	.029	.012	-.016	.212**	.095	.020	.287**	.103	1														
11	-.031	.017	.062	.013	.079	.033	.115	-.001	-.150*	-.033	1													
12	.005	.061	.071	-.027	.035	.019	.074	-.063	-.035	.056	.152*	1												
13	-.012	.010	-.080	-.020	.081	-.033	.177**	.019	-.125*	-.012	.637**	.078	1											
14	-.036	.006	.014	-.028	.036	-.020	.190**	.011	-.172**	-.014	.830**	.119	.788**	1										
15	.158*	-.009	-.156*	.063	-.064	-.012	-.009	.000	-.024	.020	-.359**	-.040	.011	-.038	1									
16	.041	.041	-.088	.059	.018	-.003	.025	-.052	.027	-.079	-.003	.033	.091	.034	-.066	1								
17	-.052	.104	-.048	-.057	-.001	-.031	.078	.039	-.080	-.046	.007	-.047	.050	.014	-.031	.288**	1							
18	.075	-.028	-.001	-.002	-.021	-.012	.001	.092	.018	.057	-.165**	.051	-.098	-.026	.128*	-.070	.017	1						
19	.140*	-.045	-.083	.013	-.060	-.021	-.005	.087	.005	.060	-.340**	.014	-.051	-.028	.648**	-.087	.006	.765**	1					
20	.118	.031	-.102	.009	-.079	-.030	-.014	.063	.013	.066	-.380**	-.027	-.037	-.040	.761**	-.086	-.018	.512**	.878**	1				
21	.096	-.007	-.114	-.008	-.088	-.002	.024	.033	.035	.040	-.374**	-.010	-.036	-.043	.683**	-.081	-.013	.552**	.859**	.799**	1			
22	.115	-.103	-.133*	.071	-.085	.005	-.042	.031	.002	-.024	-.096	-.062	-.001	-.024	.263**	-.061	-.036	.189**	.321**	.229**	.255**	1		
23	.058	-.042	-.112	.014	.061	.048	.072	.033	-.042	.066	-.161**	.034	.013	-.009	.245**	.004	.007	.070	.218**	.207**	.320**	.106	1	
24	.075	-.125*	.136*	.038	.061	.076	-.006	.125*	-.021	.053	.124*	.006	.051	.076	.122*	-.144*	-.015	.034	.102	.070	.003	-.018	-.106	1

*Table 4.9 (b): correlation matrix daily data set 2017. Significant values are denoted with * p<0.10. ** p<0.05. ***p<0.01. Strong correlations (0.60< or -0.60>) are written red.*
Legend: 1 daily return Bitcoin, 2 daily return Ripple, 3 daily return Ethereum, 4 daily return Litecoin, 5 daily return NEM, 6 liquidity growth Bitcoin, 7 liquidity growth Ripple, 8 liquidity growth Ethereum, 9 liquidity growth Litecoin, 10 liquidity growth NEM, 11 supply growth Bitcoin, 12 supply growth Ripple, 13 supply growth Ethereum, 14 supply growth Litecoin, 15 number of currencies, 16 daily return commodity index, 17 daily return S&P500, 18 exchange rate Euro, 19 exchange rate Chinese Yen, 20 natural gas price, 21 coal price, 22 negative attention, 23 regulatory attention, 24 public interest.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	1																							
2	.153*	1																						
3	.304**	.299**	1																					
4	.505**	.335**	.423**	1																				
5	.390**	.354**	.353**	.418**	1																			
6	-.030	-.115	-.039	-.175**	-.116	1																		
7	-.066	.471**	.036	.038	.065	.313**	1																	
8	-.127*	-.061	.320**	-.069	-.061	.546**	.312**	1																
9	.016	.042	.052	.385**	-.005	.439**	.227**	.359**	1															
10	.075	.043	.057	.036	.416**	.183**	.282**	.182**	.093	1														
11	.067	-.055	.006	.058	.063	.122*	.038	.133*	.156*	.103	1													
12	.070	.047	.029	.092	.090	.009	.075	-.003	.012	.006	-.004	1												
13	.030	-.061	.005	.031	.025	.151*	.027	.152*	.135*	.079	.894**	.025	1											
14	.066	-.028	.002	.059	.069	.122*	.058	.118	.146*	.108	.966**	.017	.892**	1										
16	.025	.067	-.042	.033	.000	-.042	.017	-.066	.015	-.030	-.012	-.100	-.313**	-.023	1									
17	-.033	.053	.091	.020	.057	.003	.008	-.023	-.012	.065	-.046	-.037	-.080	-.038	.112	1								
18	.015	.016	.050	.086	.004	.045	.076	.008	.017	.076	.043	-.004	.031	.057	.007	.149*	1							
19	-.036	-.003	.053	-.035	.020	.057	.029	.086	.016	.030	.020	.128*	.337**	.037	-.909**	-.115	-.006	1						
20	-.007	.000	.070	-.021	.031	.036	-.003	.074	-.016	.030	.019	.105	.336**	.040	-.923**	-.103	-.011	.921**	1					
21	.041	.024	.020	-.026	-.010	-.060	-.043	.029	-.047	.034	.024	.096	.165**	.038	-.488**	-.027	-.027	.438**	.470**	1				
22	.001	-.044	-.053	.010	-.026	-.058	.003	-.065	.002	-.029	-.015	-.080	-.248**	-.040	.769**	.072	.060	-.623**	-.771**	-.349**	1			
23	-.023	.128*	.026	.022	.019	-.047	.074	-.057	.029	-.033	-.001	-.085	-.229**	-.013	.873**	.099	.037	-.677**	-.737**	-.482**	.731**	1		
24	-.015	.128*	-.009	.029	.037	-.038	.083	-.026	.030	-.001	.009	-.063	-.230**	-.010	.845**	.078	.026	-.651**	-.714**	-.480**	.729**	.898**	1	
25	.012	.121	.033	.040	.023	-.014	.051	.008	.051	.026	-.005	-.106	-.233**	-.017	.816**	.072	.026	-.737**	-.677**	-.370**	.579**	.815**	.831**	1

*Table 4.10 (c): correlation matrix daily data set 2016-2017. Significant values are denoted with * p<0.10. ** p<0.05. ***p<0.01. Strong correlations (0.60< or -0.60>) are written red.*
Legend: 1 daily return Bitcoin, 2 daily return Ripple, 3 daily return Ethereum, 4 daily return Litecoin, 5 daily return NEM, 6 liquidity growth Bitcoin, 7 liquidity growth Ripple, 8 liquidity growth Ethereum, 9 liquidity growth Litecoin, 10 liquidity growth NEM, 11 supply growth Bitcoin, 12 supply growth Ripple, 13 supply growth Ethereum, 14 supply growth Litecoin, 15 number of currencies, 16 daily return commodity index, 17 daily return S&P500, 18 exchange rate Euro, 19 exchange rate Chinese Yen, 20 natural gas price, 21 coal price, 22 negative attention, 23 regulatory attention, 24 public interest.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	1																							
2	.139**	1																						
3	.192**	.201**	1																					
4	.565**	.285**	.278**	1																				
5	.375**	.294**	.257**	.371**	1																			
6	.012	-.087*	-.023	-.118**	-.081	1																		
7	-.055	.399**	.007	.033	.061	.266**	1																	
8	-.092*	-.076	.194**	-.057	-.061	.339**	.205**	1																
9	.027	.018	-.017	.298**	-.061	.472**	.195**	.271**	1															
10	.058	.026	.030	.011	.299**	.126**	.142**	.244**	.089*	1														
11	-.009	-.053	.026	.010	.044	.020	.051	.041	-.050	.021	1													
12	.043	.046	.049	.047	.062	.010	.072	-.035	-.011	.035	.097*	1												
13	-.008	-.058	-.053	-.005	.035	.020	.080	.071	-.021	.033	.716**	.059	1											
14	.022	-.023	.005	.024	.048	.050	.112*	.060	-.001	.041	.819**	.071	.811**	1										
15	.083	.138**	-.004	.069	.047	.079	.068	-.038	.075	-.050	-.262**	-.064	-.283**	-.057	1									
16	-.003	.049	.001	.032	.040	.003	.018	-.039	.008	-.019	-.022	-.001	.017	-.001	.059	1								
17	-.013	.051	-.007	.023	.003	.008	.075	.027	-.030	-.006	.008	-.030	.036	.029	.018	.232**	1							
18	-.030	-.042	.021	-.042	-.011	.001	-.001	.082	-.008	.049	.018	.097*	.188**	.028	-.692**	-.096*	-.004	1						
19	.071	.041	.013	.016	.020	.066	.030	.069	.032	.020	-.296**	.046	.004	-.019	-.025	-.078	.010	.629**	1					
20	.097*	.090*	-.027	.029	-.004	.047	.028	.036	.046	.018	-.406**	-.006	-.120**	-.046	.406**	-.042	-.002	.147**	.753**	1				
21	.082	.073	-.039	.035	.002	.077	.062	-.004	.076	-.018	-.407**	-.034	-.214**	-.071	.717**	-.010	.019	-.172**	.482**	.753**	1			
22	.029	.161**	.029	.052	.044	.041	.089*	-.036	.069	-.048	-.157**	-.065	-.229**	-.039	.874**	.064	.028	-.618**	-.169**	.185**	.557**	1		
23	.028	.163**	.010	.053	.063	.043	.100*	-.019	.064	-.024	-.146**	-.045	-.224**	-.035	.845**	.058	.026	-.610**	-.192**	.158**	.539**	.917**	1	
24	.070	.157**	.068	.071	.073	.105*	.086	.013	.093*	-.022	-.190**	-.060	-.246**	-.039	.893**	.027	.026	-.591**	.034	.345**	.599**	.827**	.823**	1

Daily correlations

The variables regarding *supply growth* are in various combinations correlated with each other across all panels. For example *supply growth Bitcoin* is strong and positive correlated with *supply growth Litecoin* with a Pearson correlation coefficient of 0.830 at a 95% significance level. The correlations regarding *supply growth* are always positive. Possibly indicating that the supply growth of these cryptocurrencies move in tandem. This has no effect on the data analysis as these variables are not tested simultaneously.

First of all, the variables used in model 1 (cost-based) are reviewed. *Natural gas price* and *coal price* are strongly correlated during 2016 and 2016-2017. This strong correlation between *natural gas price* and *coal price* of .799 (2016) and .753 (2016-2017) seems logical given the fact that both commodities are substitutes (for the production of energy). This strong correlation has a great impact on explanatory power and robustness of model 1 (cost-based), since only one variable can be used simultaneously when testing the data for 2016 and 2016-2017. Resulting in only one variable to test the model, which is seen as a limitation for this research (see section 7.1). Despite the fact that the cost-based variables are not strongly correlated in 2017, *coal price* is not adopted in this model due to its strong correlation with both control variables.

Secondly, the variables used in model 2 (supply and demand) are reviewed. Most strong and significant correlations can be found during the 2017 and 2016-2017 period. Similar to Wang and Vergne (2017) are the attention related variables strongly positively correlated. Whereas Wang and Vergne indicate that *public interest* and *negative attention* have a Pearson correlation coefficient of .860 (95% significant), I find almost similar Pearson correlation coefficients of .815 and .827 at similar significance. Furthermore *regulatory attention* shows also strong positive correlations with both *public interest* and *negative attention*. However, these strong correlations are only due in 2017 and during the total period. Possibly indicating that certain types of attention (positive or negative) have a different impact in an ordinary year (2016), while it does have a similar impact during a year of rapid growth (2017). Nevertheless, these variables are not simultaneously when testing 2017's and 2016-2017's dataset due to this strong correlations. However, the variables are used simultaneously to when testing the data 2016. Additionally, *number of currencies* shows similar behaviour and correlations during all three data panels. *Number of currencies* is correlated with *exchange rate Euro, exchange rate Chinese Yen, Negative Attention, Regulatory Attention and Public Interest.* Again, these correlations are only due in 2017 and 2016-2017. Hence, these variables are not used simultaneously when testing these data sets.

Both control variables, *exchange rate Euro* and *exchange rate Chinese Yen*, show strong correlations across all panels. This correlation is understandable given the fact that an exchange rate involves two currencies, including the dollar for both variables. Hence, a weak or strong dollar influences both variables. All Pearson correlation coefficients show that these variables are positively correlated: .629, .765 and .925. All correlations are significant at a 95% level. Thus, the control variables must be used interchangeably. Furthermore, in 2017, both control variables are strongly correlated with several variables used in model 2 (for example *number of currencies* and *public interest*). Hence, no control variable is used in this case.

*Table 4.11 (a): correlation matrix weekly data set 2016. Significant values are denoted with * p<0.10. ** p<0.05. ***p<0.01. Strong correlations (0.60< or -0.60>) are written red.*

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	**weekly return cryptocurrency**	1												
2	**weekly liquidity growth cryptocurrency**	.416**	1											
3	**weekly supply growth cryptocurrency**	.152	.098	1										
4	**number of currencies**	-.422**	-.161	-.234	1									
5	**weekly return commodity index**	.102	-.066	.224	-.098	1								
6	**weekly return S&P500**	-.313*	-.163	.131	.006	.336*	1							
7	**exchange rate Euro**	-.013	.087	-.121	.129	-.118	.109	1						
8	**exchange rate Chinese Yen**	-.257	-.075	-.167	.637**	-.184	.028	.769**	1					
9	**natural gas price**	-.294*	-.042	-.200	.756**	-.186	-.090	.509**	.877**	1				
10	**coal price**	-.301*	-.073	-.202	.684**	-.122	-.034	.552**	.851**	.794**	1			
11	**negative attention**	-.285*	-.183	-.210	.263	-.119	.091	.220	.331*	.241	.243	1		
12	**regulatory attention**	-.185	-.038	-.056	.245	.182	.173	.081	.204	.185	.318*	.106	1	
13	**public interest**	-.205	.000	-.018	.232	-.086	-.156	.119	.246	.272	.122	.144	-.110	1

*Table 4.12 (b): correlation matrix weekly data set 2017. Significant values are denoted with * p<0.10. ** p<0.05. ***p<0.01. Strong correlations (0.60< or -0.60>) are written red.*

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	**weekly return cryptocurrency**	1												
2	**weekly liquidity growth cryptocurrency**	.478**	1											
3	**weekly supply growth cryptocurrency**	.271	-.047	1										
4	**number of currencies**	-.004	-.018	-.374**	1									
5	**weekly return commodity index**	-.134	-.170	.001	.102	1								
6	**weekly return S&P500**	.040	-.067	.132	-.193	.018	1							
7	**exchange rate Euro**	.114	.080	.400**	-.912**	-.190	.168	1						
8	**exchange rate Chinese Yen**	.176	.091	.369**	-.928**	-.130	.162	.922**	1					
9	**natural gas price**	.060	-.002	.349*	-.472**	-.022	.041	.427**	.451**	1				
10	**coal price**	-.192	-.211	-.167	.759**	.073	-.078	-.612**	-.777**	-.307*	1			
11	**negative attention**	.145	-.022	-.272	.873**	.012	-.102	-.683**	-.738**	-.481**	.722**	1		
12	**regulatory attention**	.157	.034	-.238	.845**	.027	-.203	-.653**	-.710**	-.455**	.716**	.898**	1	
13	**public interest**	.175	.104	-.250	.817**	.067	-.145	-.765**	-.688**	-.369**	.562**	.799**	.828**	1

*Table 4.13 (a): correlation matrix weekly data set 2016-2017. Significant values are denoted with * p<0.10. ** p<0.05. ***p<0.01. Strong correlations (0.60< or -0.60>) are written red.*

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	**weekly return cryptocurrency**	1												
2	**weekly liquidity growth cryptocurrency**	.442**	1											
3	**weekly supply growth cryptocurrency**	.173	.016	1										
4	**number of currencies**	.136	-.013	-.324**	1									
5	**weekly return commodity index**	-.006	-.100	.135	.002	1								
6	**weekly return S&P500**	-.144	-.120	.132	-.096	.256**	1							
7	**exchange rate Euro**	.014	.072	.256**	-.693**	-.119	.127	1						
8	**exchange rate Chinese Yen**	.094	.019	.036	-.029	-.153	.054	.631**	1					
9	**natural gas price**	.015	-.013	-.123	.417**	-.143	-.077	.140	.749**	1				
10	**coal price**	-.012	-.074	-.239*	.717**	-.076	-.060	-.172	.471**	.756**	1			
11	**negative attention**	.205*	-.018	-.268**	.874**	-.018	-.058	-.620**	-.170	.194*	.557**	1		
12	**regulatory attention**	.218*	.029	-.233*	.845**	.013	-.101	-.611**	-.192	.170	.539**	.917**	1	
13	**public interest**	.254**	.063	-.241*	.904**	-.006	-.099	-.608**	.038	.377**	.616**	.831**	.830**	1

Weekly correlations

Similar to the daily results, the data of the ordinary year (2016) includes less significant strong correlations than the year of rapid growth (2017). No significant correlations can be found when reviewing the Pearson correlation coefficients of the technical analysis related variables. However, some considerations are made for the variables included in model 1 (costs) and model 2 (supply and demand). First of all, *coal price* and *natural gas price* are across the 2016 and 2016-2017 panel strongly (positively) correlated. High Pearson correlation coefficients are due; .794 (2016) and .756 (2016-2017). However, *price coal* and *natural gas price* are not strongly correlated in 2017. Hence, both cost representing variables are tested in this model. Both *price coal* and *price natural gas* are strongly correlated with *exchange rate Chinese Yen*. This control variable is therefore not used.

Secondly, the variables used in model 2 (supply and demand) are, similar to daily data, not correlated when using the 2016 data and strongly correlated when using the 2017 data. Hence, in 2016 all variables of model 2 can are tested simultaneously. While some considerations are made for the 2017 and 2016-2017 panel. In 2017 *number of currencies, public interest, negative attention* and *regulatory attention* cannot be used simultaneously. Again 2017's data is in line with previous research of Wang and Vergne (2017). *Number of currencies* shows most strong correlations when analysing the weekly data. However, *public interest* is also five times strongly correlated with other variables. For some reason are both control variables strongly correlated with the trend related variables (*public interest, attention*). This issue is resolved by removing both control variables in this model. Model 2 does need similar alterations when 2016-2017 data compared to 2017. No trend related variable can be used simultaneously. However, *exchange rate Chinese Yen* can be used as control variable instead of *exchange rate Euro*.

5 RESULTS

This chapter includes the results of the regression analysis of five cryptocurrencies. First an analysis of the results per cryptocurrency is given. Subsequently the combined (weekly) data is explained. The last paragraph compares differences among cryptocurrencies. Some observations are ruled out due to missing values. However, this number is too low to affect the statistical significance as the minimum of 20 observations per variable is still met (section 4.1). The results can be found in tables 5.1 until 5.6. The regression tables include standardized beta coefficients rather than unstandardized beta coefficient. I choose to use standardized beta coefficients as they are more suitable to compare the relative importance of coefficients (Freedman, 2009). The raw data (including the unstandardized beta coefficients and the variance inflation factors) can be found in appendix 9.6.

5.1 BITCOIN

At first glance, little significant relationships can be found in table 5.1. Additionally low or negative adjusted R squared values indicate that all models have little or no explanatory power. This non-robust pattern is in line with Chatterjee, et al. (2017), who recognized that data is often not significant and show spurious results. In 2017 (rapid growth) no positive adjusted R squared values and no significant associations are due. This year is therefore not discussed below. The lack of explanatory power and significant correlations can be caused by the extraordinary characteristics of this year. However, this phenomena is appears to be less for the altcoins (see sections 5.2 – 5.5). Nevertheless all three models are reviewed. First of all, model 1 (cost-price) has, compared to the other models, average explanatory power. Model 1 shows adjusted R squared values of .006 (2016) and .004 (2016-2017). Hence, the explanatory power of this model is low. Which is in line with previous research of Hayes (2017). No weekly data is used in model 1, so low autocorrelation is expected. This is confirmed by the Durbin Watson value of 1.916 which is between the boundaries of 1.5 and 2.5. No significant relationships can be recognized. Therefore I reject hypothesis 1 in regards to Bitcoin due to a lack of significance.

Secondly, model 2 (supply and demand) is discussed. Model 2 yields the highest explanatory power compared to other models in 2016 and 2016-2017. *Number of currencies* (thus new entries) does have a positive influence on the price formation of Bitcoin across all panels. However, solely this variable shows solely two significant relationships; model 4 – 2016 (.188 at 90% significance) and model 2 – 2016-2017 (0.096 at 95% significance. This result is not in line with hypothesis 2a nor with results of Luchansky and Monks (2009) who showed that additional competition for commodities often has a negative influence on price. Therefore I reject hypothesis 2a in regards to Bitcoin due to a lack of significant correlations and, moreover, significant positive correlations. Additionally, the variables that represented substitutes (*daily return U.S. commodity index* and *daily return S&P500*) show no significant relationship. Hence I reject hypothesis 2b in regards to Bitcoin as there is no consensus nor significant relationships. Additionally, model 2 includes three weekly variables (*number of currencies, negative attention* and *regulatory attention*). Hence, it could be subject to autocorrelation. However, this is not the case as its Durbin Watson value of 1.972 which is between the boundaries of 1.5 and 2.5.

Thirdly, technical analysis related variables are reviewed. Model 3 (technical analysis) yields relatively high adjusted R squared values of .014 (2016) and .004 (2016-2016). Nevertheless, these adjusted R squared values are extremely low compared to previous research to asset price predictability by Bettman, et al. (2009) which yielded adjusted R squared values of .755 including two more variables (prior prices). Nevertheless, both *supply growth Bitcoin* and *liquidity growth Bitcoin* show no significant influence regarding *daily return Bitcoin*. Hence, due to a lack of significant relationships, I reject both hypothesis 4a and 4b in regards to Bitcoin.

*Table 5.1 Bitcoin regression table. Bitcoin daily return as dependent variable. Whereas the numbers not in parentheses are the standardized betas and the numbers within parentheses is the standard error. Significance is denoted with * p<0.10. ** p<0.05. ***p<0.01. Model 1 is cost-based, model 2 is supply and demand, model 3 is technical analysis and model 4 includes all variables.*

	2016				**2017**				**2016-2017**			
MODEL	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
VARIABLE												
NUMBER OF CURRENCIES		.102		.188*		.030		.061		.096**		.080
		(.000)		(.000)		(.000)		(.000)		(.000)		(.000)
DAILY RETURN U.S. COMMODITY INDEX		.087		.086		-.036		-.038		.002		.003
		(.258)		(.258)		(.468)		(.470)		(.264)		(.265)
DAILY RETURN S&P500		-.071		-.068		.017		.020		-.016		-.015
		(.236)		(.236)		(.615)		(.618)		(.279)		(.280)
NEGATIVE PUBLICITY		.074		.071								
		(.000)		(.000)								
REGULATORY PUBLICITY		.026		.020								
		(.001)		(.001)								
PUBLIC INTEREST		.069		.062								
		(.006)		(.006)								
NATURAL GAS PRICE	.107			-.077	.071			.067	.065			.041
	(.003)			(.006)	(.015)			(.015)	(.000)			(.006)
SUPPLY GROWTH BITCOIN		.028	.016	.022		.064	.072	.067		.042	.013	.045
		(7.417)	(7.138)	(7.382)		(23.459)	(23.527)	(23.736)		(9.015)	(8.669)	(9.167)
LIQUIDITY GROWTH BITCOIN			.077	.067			-.037	-.032			.006	-.001
			(.004)	(.004)			(.005)	(.005)			(.003)	(.003)
EXCHANGE RATE EURO	.021			.086	-.068		-.036					
	(.078)			(.089)	(.065)		(.058)					
EXCHANGE RATE		.055	.147						.035	.086*	.074	.056
CHINESE YEN		(.014)	-0.011						(.011)	(.010)	(.010)	(.018)
N	258	259	259	258	258	259	259	258	516	519	519	516
ADJUSTED R2	.006	.015	.014	.017	-.002	-.009	-.004	-.012	.004	.004	-.001	.001
DURBIN WATSON	1.918	1.990	1.941	2.004	1.823	1.822	1.798	1.828	1.811	1.842	1.830	1.818

5.2 RIPPLE

Table 5.2 shows the results of the regression analysis with the *daily return Ripple* as dependent variable. Only a few significant relationships and relatively low and negative adjusted R squared values can be found in table 5.2. Model 3 yields the highest R squared values indicating that technical analysis has the highest explanatory power in regards to Ripple's price movement. Furthermore three considerations can be made. First of all, model 1 (cost-based) has, compared to the other models, the lowest adjusted R squared values of -.004, -.007 and .002. Furthermore the variable *natural gas price* shows once a significant relationship with *daily return Ripple*. A positive relationship with a coefficient of .113 at a 90% significance when testing model 4 during 2017. *Price coal* on the other hand shows a negative relationship at 95% significance during 2016-2017. This is not in line with the theory (Noble & Gruca, 1999; Kotler, et al., 2005; Hinterhuber, 2016). Still, this significant relationship is only present during the overall period. The overall period is, given its divergent characteristics, not suitable to accept hypotheses. Hence I reject hypothesis 1 in regards to Ripple due to a lack of significant correlations and significant positive relationships in 2016.

Secondly, model 2 (supply and demand) shows low, but positive, adjusted R squared values of .016, .006 and .027. Weekly available data is used in this model. Nevertheless, no model is subject to autocorrelation since the Durbin Watson statistics remains between the boundaries of 1.5 and 2.5. The variables that represent substitutes (*daily return U.S. commodity index* and *daily return S&P500*) show one significant relationship. A positive relationship with a beta of .108 at 90% significance can be recognized in 2016. Nevertheless, no significant (negative) relationships can be found in table 5.2. Hence I reject hypothesis 2b in regards to Ripple as there are no negative relationships nor significant relationships. Additionally, the variable *supply growth Ripple* shows no significant correlations in model 2 (or model 4). The trend related variables, *negative attention, regulatory attention* and *public interest*, indicate negative relationships in 2016 and positive relationships in 2017 and 2016-2017. Whereas *public interest* shows a negative association in 2016 (-.140 and -.137), both at 95% significance level. *Negative attention* shows a positive relation in 2017 and during the total period (.129, .146, .173 and .238) at 95% or 99% significance level. Possibly indicating that *public interest,* due an aversion for new technologies or prejudices, in an ordinary year results in less buyers and thus a lower price. The results of 2017 (year of rapid growth) on the other hand show that negative attention does not have a negative influence on price. This is not in line with the theory and is possibly only due in an extraordinary year as 2017. Overall, there is a significant relationship between *public interest* and *daily return Ripple*, so I accept hypothesis 3a. Additionally I reject hypothesis 3b as negative attention does not have a negative influence on the price movement of Ripple. Further research can point if this result holds during following, ordinary, years.

Thirdly, the technical analysis related variables are assessed. Compared to the other models, model 3 yields high adjusted R squared values. However, solely *liquidity growth Ripple* shows significant (at 99%) relationships *daily return of Ripple*. I therefore accept hypothesis 4a. The significant correlation *liquidity growth Ripple* with price indicates that once the volume increases, the price does too. This phenomena is stronger in 2017 (year of rapid growth). This is not in line with the theory of Blume, et al. (1994), who suggest that volume normally results in a 'V' shaped pattern (either positive or negative). However, on average the results should be just as often negative as positive (section 3.5.2). The fact that this phenomena is only positive strengthens the assumption that cryptocurrency (at least in case of Ripple) is currently in a growth stage that shows little signs of decay. On the other hand, the variable that measures scarcity (or lack of it), *supply growth Ripple*, is not significant related with the daily return of Ripple. I therefore reject hypothesis 4b.

*Table 5.2: Ripple regression table. Ripple daily return as dependent variable. Whereas the numbers not in parentheses are the standardized betas and the numbers within parentheses is the standard error. Significance is denoted with * p<0.10. ** p<0.05. ***p<0.01. Model 1 is cost-based, model 2 is supply and demand, model 3 is technical analysis and model 4 includes all variables.*

	2016				**2017**				**2016-2017**			
MODEL	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
VARIABLE												
NUMBER OF CURRENCIES		.080		-.073								
		(.000)		(.000)								
DAILY RETURN U.S. COMMODITY INDEX		-.017		-.012		.041		.042		.034		.032
		(.373)		(.365)		(.737)		(.652)		(.408)		(.379)
DAILY RETURN S&P500		.109*		.091		.005		-.028		.039		.011
		(.341)		(.334)		(.971)		(.861)		(.431)		(.401)
NEGATIVE PUBLICITY		-.100		-.089		.129**		.146**		.173***		.238***
		(.001)		(.001)		(.000)		(.000)		(.000)		(.000)
REGULATORY PUBLICITY		-.060		-.077								
		(.001)		(.001)								
PUBLIC INTEREST		-.140**		-.137**								
		(.009)		(.008)								
NATURAL GAS PRICE	.061			.184	.030			.113*				
	(.005)			(.008)	(.023)			(.021)				
COAL PRICE									.066			-.154**
									(.000)			.000
SUPPLY GROWTH RIPPLE		.067	.044	.053		.059	.014	.015		.055	.016	.021
		(1.118)	(1.096)	(1.096)		(2.245)	(2.011)	(1.997)		(1.236)	(1.152)	(1.149)
LIQUIDITY GROWTH RIPPLE			.225***	.220***			.471***	.465***			.397***	.382***
			(.003)	(.003)			(.004)	(.004)			(.003)	(.003)
EXCHANGE RATE EURO	-.059			-.092	-.014		-.018					
	(.113)			(.126)	(.104)		(.083)					
EXCHANGE RATE CHINESE YEN		-.040	-.045						.015	.070	.029	.150***
		(.020)	(.015)						(.017)	(.015)	(.014)	(.020)
N	258	259	259	258	258	259	259	258	510	519	519	510
ADJUSTED R2	-.004	.016	.045	.065	-.007	.006	.213	.225	.002	.027	.156	.178
DURBIN WATSON	1.812	1.852	1.831	1.877	1.807	1.853	1.923	1.969	1.805	1.841	1.878	1.944

5.3 ETHEREUM

Table 5.3 shows the results of the regression analysis with the *daily return Ethereum* as dependent variable. Little significant relationships and relatively low R squared values are found in table 5.3. Both model 2 (supply and demand) and model 3 (technical analysis) distinguish themselves with higher explanatory power during 2016 (supply and demand) and 2017 (technical analysis) compared to other models. There is no model subject to autocorrelation since the Durbin Watson statistics remain between the boundary of 1.5 and 2.5. Additionally, some considerations can be made for each model. First of all, the variable *natural gas price* is only once significant in all models and panels. *Natural gas price* is significant at 90% level, this shows a negative relationship of -.137 in 2016. This negative association is in not line with the theory. Furthermore, this negative relationship is not robust throughout 2016 and no significant relationships can be found in 2017. Additionally, *coal price* does show a negative and significant association with *daily return Ethereum*. Hence I therefore reject hypothesis 1 in regards to Ethereum due a lack of significant relationships and negative relationships.

Secondly, model 2 (supply and demand) has, compared to the other models, a high adjusted R squared value in 2016 of .044. Nevertheless, most variables do not have a significant relationship with *daily return Ethereum*. Which explains the low explanatory power compared to the model of Luchansky and Monks (2009). I therefore reject hypothesis 2b as both *daily return U.S. commodity index* as *daily return S&P500* do not show any significant relationship with *daily return Ethereum*. *Public interest*, however, is positively associated with *daily return Ethereum* during 2016 with .138 and .128 betas at 95% significance. This positive influence is line with findings of Wang and Vergne (2017) who investigated data from 2014 and 2015. I therefore accept hypothesis 2a in regards to Ethereum for 2016. The expected negative influence of *regulatory attention* on the other hand is not due. I therefore also reject hypothesis 3b for all periods.

Thirdly, model 3 (technical analysis) shows high adjusted R squared values throughout all panels compared to other models. Especially *liquidity growth Ethereum* during 2017 and the overall period shows, at 99% significance, positive relationships with *daily return of Ethereum*. I therefore accept hypothesis 4a. This significance might be caused by the rapid growth, similar to Ripple, that Ethereum and other cryptocurrencies experienced in 2017. Resulting in volume always indicating an increase in price. The variable that measures scarcity (or lack of it), *supply growth*, is not significant related to *daily return Ethereum*. I therefore accept hypothesis 4b in regards to Ethereum.

5.4 LITECOIN

Table 5.4 shows the results of the regression analysis with the *daily return Litecoin* as dependent variable. Little significant relationships and relatively low adjusted R squared values can be found in table 5.4. This phenomena is strongest in 2016, as not a single model yields a positive adjusted R squared value. Still some considerations are made. First of all, both model 1 (cost-based) and model 2 (supply and demand) yield negative or low adjusted R squared values. Additionally, no significant relationships can be found across all years. This absence of significant relationships is comparable to the results of Bitcoin, but not to Ripple and Ethereum. Bitcoin and Litecoin are the oldest cryptocurrencies included in this research. Additionally, both Bitcoin and Litecoin experienced the least annual growth of the five included cryptocurrencies. These characteristics might suggest that Bitcoin and Litecoin are more mature. Therefore possibly less influenced by trends or competition. Further research can point out if this conclusion holds when comparing a larger sample of cryptocurrencies. Nevertheless, there are no significant relationships between *natural gas price, number of currencies, daily return U.S. commodity index, daily return S&P500, negative publicity* and *public interest*. Hence, I reject hypothesis 1, 2b, 3a, 3b and 3c in regards to Litecoin due to a lack of significant relationships.

*Table 5.3: Ethereum regression table. Ethereum daily return as dependent variable. Whereas the numbers not in parentheses are the standardized betas and the numbers within parentheses is the standard error. Significance is denoted with * p<0.10. ** p<0.05. ***p<0.01. Model 1 is cost-based, model 2 is supply and demand, model 3 is technical analysis and model 4 includes all variables.*

	2016				**2017**				**2016-2017**			
MODEL	1	2	3	4	1	2	3	4	1	2	3	4
VARIABLE												
NUMBER OF CURRENCIES		-.166**		-.168								
		(.000)		(.000)								
DAILY RETURN U.S. COMMODITY INDEX		-.065		-.063		.087		.091		.004		.012
		(.684)		(.686)		(.726)		(.690)		(.501)		(.492)
DAILY RETURN S&P500		-.033		-.035		.037		.036		-.007		-.012
		(.623)		(.624)		(.957)		(.909)		(.530)		(.520)
NEGATIVE PUBLICITY		-.100		-.100								
		(.001)		(.001)								
REGULATORY PUBLICITY		-.054		-.049		-.016		-.015		.001		.092
		(.001)		(.001)		(.000)		(.000)		(.000)		(.000)
PUBLIC INTEREST		.138**		.128**								
		(.016)		(.016)								
NATURAL GAS PRICE	-.137*			.036	-.007			.014				
	(.009)			(.015)	(.023)			(.022)				
COAL PRICE									-.056			-.146**
									(.000)			(.000)
SUPPLY GROWTH ETHEREUM		-.074	-.086	-.077		.007	-.060	-.045		-.052	-.067	-.088*
		(9.294)	(9.375)	(9.336)		(14.056)	(13.857)	(13.532)		(7.801)	(7.442)	(7.787)
LIQUIDITY GROWTH ETHEREUM			.092	.064			.325***	.325***			.198***	.194***
			(.005)	(.005)			(.005)	(.005)			(.004)	(.004)
EXCHANGE RATE EURO	.068			.002	.062		.045					
	(.208)			(.236)	(.102)		(.092)					
EXCHANGE RATE CHINESE YEN		.045	-.096						.035	.014	.000	.082
		(.036)	(.028)						(.021)	(.018)	(.018)	(.026)
N	258	259	259	258	258	259	259	258	510	519	519	510
ADJUSTED R2	.006	.044	.011	.040	-.004	-.006	.096	.092	-.001	-.007	.036	.037
DURBIN WATSON	2.040	2.092	2.065	2.147	1.749	1.760	1.891	1.899	1.903	1.871	1.946	1.996

Lastly the model 3 (technical analysis) does show positive adjusted R squared values during 2017 and 2016-2017. This high explanatory power is caused by *liquidity growth Litecoin*. This variable has high betas of .385 and .384, both at 99% significance level. I therefore accept hypothesis 4a. Similar to Ripple and Ethereum, this significance might be caused by the rapid growth that cryptocurrencies experienced in 2017. S*upply growth Litecoin*, is not significant related with *daily return Litecoin*. I therefore reject hypothesis 4b in regards to Litecoin.

5.5 NEM

Table 5.5 shows the results of the regression analysis with the *daily return NEM* as dependent variable. There is no model subject to autocorrelation as all Durbin Watson statistics remain between the boundaries of 1.5 and 2.5. Considerations are made for each model. First of all, both model 1 (cost-based) and model 2 (supply and demand) yield negative adjusted R squared values. Indicating that these models do not have any explanatory power. Whereas the absence of explanatory power of the cost-based model is in line with both previous results and previous research by Hayes (2017). The absence of explanatory power of the supply and demand requires more explanation. NEM has a similar software protocol (light), nature (commodity-like) and age (2 years) as Ethereum. Yet its behaviour is completely different. Possible due to the fact that NEM is partially decentralized and Ethereum is completely decentralized. However, different thoughts, such as the fact that NEM has a fixed number of circulating supply or the fact that NEM is Asian and Ethereum is European can also be a likely explanation. This might be a topic for further research. Nevertheless, there are no significant relationships between *natural gas price, number of currencies, daily return U.S. commodity index, daily return S&P500, negative publicity* and *public interest*. Hence, I reject hypothesis 1, 2a, 2b, 3a, 3b and 3c in regards to NEM due to a lack of significant relationships.

Lastly, model 3 (supply and demand) shows, similar to other rapid growing cryptocurrencies (Ethereum and Ripple, see section 4.1), the highest adjusted R squared values throughout all panels compared to other models. *Liquidity growth NEM* shows, at 99% significance, positive relationships with *daily return NEM*. This trend is strongest during 2017. I therefore accept hypothesis 4a. This significance is in line with previous cryptocurrencies described. The variable *supply growth NEM* is left out of this regression analysis since NEM does have a fixed amount of circulating supply, hence it experiences no supply growth.

5.6 WEEKLY CRYPTOCURRENCY

Table 5.6 contains the regression results with *weekly return cryptocurrency* as dependent variable. The results of 2017 and model 1 from the 2016-2017 period cannot be used as these models are subject to autocorrelation. The Durbin Watson statistic is below the boundary of 1.5. The presence of autocorrelation can result in, among others, too small standard errors and too large t-statistics (Freedman, 2009). The results of these models are therefore not considered for hypothesis testing. Furthermore, the weekly data has, compared to the daily regression results, high adjusted R squared values. This might be due to less divergent data input. Nevertheless, these adjusted R squared values are two till three times smaller compared to existing models of Luchansky and Monks (2009), Hayes (2017) and Bettman, et al. (2009). Especially model 1 (cost-based) yields low adjusted R squared and lacks significant correlations, but this is in line with previous research of Hayes. Nevertheless, *natural gas price* has, contrary to hypothesis 1 (thus theory), a negative influence on the average weekly return of the included cryptocurrencies during 2016. Both betas are significant at 95% and 90%. Furthermore, the cost-based pricing model also not applies during a year of rapid growth (2017). Hence, I reject hypothesis 1 for cryptocurrency.

*Table 5.4: Litecoin regression table. Litecoin daily return as dependent variable. Whereas the numbers not in parentheses are the standardized betas and the numbers within parentheses is the standard error. Significance is denoted with * p<0.10. ** p<0.05. ***p<0.01. Model 1 is cost-based, model 2 is supply and demand, model 3 is technical analysis and model 4 includes all variables.*

	2016				**2017**				**2016-2017**			
MODEL	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
VARIABLE												
NUMBER OF CURRENCIES		.078		.143								
		(.000)		(.000)								
DAILY RETURN U.S. COMMODITY INDEX		.094		.090		.007		.011		.027		.021
		(.319)		(.321)		(.655)		(.608)		(.361)		(.346)
DAILY RETURN S&P500		-.077		-.073		.081		.078		.014		.026
		(.291)		(.293)		(.865)		(.804)		(.381)		(.366)
NEGATIVE PUBLICITY		.072		.060								
		(.001)		(.001)								
REGULATORY PUBLICITY		.006		.003								
		(.001)		(.001)								
PUBLIC INTEREST		.051		.046		.038		.022		.072		.023
		(.007)		(.007)		(.005)		(.005)		(.003)		(.003)
NATURAL GAS PRICE	.014			-.134	-.012			.002	.036			.014
	(.004)			(.007)	(.021)			(.019)	(.004)			(.005)
COAL PRICE												
SUPPLY GROWTH LITECOIN		-.031	-.016	-.019		.055	.004	.001		.026	.025	.027
		(6.306)	(6.363)	(6.428)		(13.372)	(12.483)	(12.573)		(7.249)	(6.916)	(6.958)
LIQUIDITY GROWTH LITECOIN			.069	.067			.385***	.384***			.298***	.297***
			(.004)	(.004)			(.005)	(.005)			(.003)	(.003)
EXCHANGE RATE EURO	-.009			.042	-.032		-.041		-.050	.002	-.041	-.030
	(.095)			(.110)	(.092)		(.076)		(.057)	(.070)	(.054)	(.076)
EXCHANGE RATE CHINESE YEN		-.060	.012									
		(.017)	(.013)									
N	258	259	259	258	258	259	259	258	517	519	519	517
ADJUSTED R2	-.008	-.009	-.006	-.010	-.006	-.004	.140	.136	-.001	-.003	.086	.082
DURBIN WATSON	2.059	2.092	2.049	2.095	1.924	1.939	2.067	2.039	1.952	1.962	2.026	2.011

Furthermore, model 2 (supply and demand) shows relative higher adjusted R squared values compared to other models in 2016. Indicating that trends and the behaviour of substitutes yield more explanatory power on a weekly basis than on a daily basis. As expected *number of currencies* (thus new entries) have a negative influence on *daily return cryptocurrency* (-.303 at 95% significance level). Additionally *daily return S&P500* is negatively associated with *daily return cryptocurrency.* This is in line with the findings of Hong (2017), who stated that cryptocurrencies are a valuable addition to a traditional portfolio due to its opposite price movement and high returns. Nevertheless, trend related variables are not significant correlated with *daily return cryptocurrency.* Hence, it seems that cryptocurrencies prices are negatively influenced by new entries and substitutes. Hence, I accept hypothesis 2a and 2b. I reject hypothesis 3a, 3b and 3c on the other hand as none of the trends has a significant influence. The results of 2017 are subject to autocorrelation. Nevertheless, the positive relationship of *negative attention* was also present in daily results and seems therefore likely. I therefore reject hypothesis 3b in regards to cryptocurrency as a whole during 2017. This contradicting outcome is in line with previous research of Wang and Vergne (2017). Possibly indicating any type of attention during a year of rapid growth drives the price. Further research can reveal whether this phenomena holds during more 'ordinary' years. Other variables, such as *supply growth*, did not show robust results in previous regression tables, I therefore do not make any statements regarding these results as they may be biased due to the autocorrelation.

Model 3 (technical analysis) on the other hand yields slightly lower adjusted R squared values in 2016 compared to model 2 (supply and demand). Whilst it shows high adjusted R squared values in 2017, which is similar to the individual regression results. This high adjusted R squared value is mainly due the significant and positive relationships with *liquidity growth cryptocurrency*. Additionally the *supply growth cryptocurrency* contributes to significant correlations in 2017. However, this outcome is questionable given the fact that these models are subject to autocorrelation. This phenomena is not present during an ordinary year (2016). Possibly indicating that this positive correlation is only due during years of high growth.

5.7 DIFFERENCES AND SIMILARITIES

The hypotheses are repeated and answered in this section in regards to all cryptocurrencies. Additionally differences and similarities are recognized regarding the five investigated cryptocurrencies. Overall it seems that daily data is often too noisy to answer or reject hypotheses. Furthermore, the noisiness of the data resulted in the rejection of most hypotheses. Nevertheless, the weekly data was more in line with the hypotheses. Especially the results of 2016 (for both weekly and daily dataset) are in line with previous theories. The year 2017 proves to be a special year with results that are not in line with previous theories.

Hypothesis 1: the price of cryptocurrencies is negatively influenced by energy prices.

Beforehand, it seemed likely that cryptocurrencies that use less computing power (thus a light blockchain) are less influenced by cost price. Bitcoin and Litecoin should therefore be influenced most by costs. Nevertheless, both Bitcoin and Litecoin are not influenced by cost-based variables. Ripple and Ethereum on the other hand show most negative (and significant) relationships with cost-based variables. Possibly indicating that investing in Ripple and Ethereum becomes more popular when energy prices are high and Ripple and Ethereum have low energy costs. the price movement of Ripple and Ethereum can be explained by cost-based pricing. Additionally, *natural gas price* and *coal price* are mostly insignificant associated with the cryptocurrencies' weekly returns. Hence, I reject hypothesis 1 for all cryptocurrencies due to the low explanatory power, negative relationships and a lack of significant correlations.

*Table 5.5: NEM regression table. NEM daily return as dependent variable. Whereas the numbers not in parentheses are the standardized betas and the numbers within parentheses is the standard error. Significance is denoted with * p<0.10. ** p<0.05. ***p<0.01. Model 1 is cost-based, model 2 is supply and demand, model 3 is technical analysis and model 4 includes all variables.*

	2016				2017				2016-2017			
MODEL	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
VARIABLE												
NUMBER OF CURRENCIES		-.303**										
		(.000)										
WEEKLY RETURN U.S.		.197		.207		-.138		-.053		.006		.039
COMMODITY INDEX		(.859)		(.818)		(2.189)		(1.925)		(.969)		(.880)
WEEKLY RETURN S&P500		-.406***		-.395***		.022		.056		-.165*		-.120
		(.926)		(.897)		(2.157)		(1.874)		(1.022)		(.924)
NEGATIVE PUBLICITY		-.127		-.097		.240*		.293**		.267***		.274***
		(.003)		(.003)		(.001)		(.001)		(.000)		(.000)
REGULATORY PUBLICITY		-.093		-.117								
		(.004)		(.004)								
PUBLIC INTEREST		-.190		-.196								
		(.068)		(.064)								
NATURAL GAS PRICE	-.388**			-.287*	.013			.081	.014			-.005
	(.028)			(.026)	(.109)			(.096)	(.025)			(.022)
SUPPLY GROWTH		.075	.108	.069		.333**	.315**	.339**		.266***	.183**	.250***
CRYPTOCURRENCY		(15.285)	(15.595)	(14.409)		(21.504)	(19.924)	(19.325)		(13.853)	(12.744)	(12.474)
LIQUIDITY GROWTH			.409***	.304**			.496***	.495***			.443***	.432***
CRYPTOCURRENCY			(.019)	(.017)			(.022)	(.022)			(.015)	(.015)
EXCHANGE RATE EURO	.184	.161	-.036	.236*	.109		-.051		.012		-.065	
	(.665)	(.538)	(.560)	(.589)	(.469)		(.391)		(.329)		(.299)	
N	255	255	255	255	255	255	255	255	515	515	515	515
ADJUSTED R2	.076	.261	.136	.335	-.027	.072	.274	.303	-.019	.089	.203	.264
DURBIN WATSON	2.237	2.129	2.288	2.149	1.305	1.313	1.444	1.488	1.446	1.579	1.601	1.715

Hypothesis 2a: the price of cryptocurrencies is negatively influenced by new entries.
The variable for new entries is solely tested for Bitcoin. Nevertheless, it showed rather positively relationships. Indicating that Bitcoin is not influenced by new entries. Perhaps because the market for cryptocurrencies is not yet saturated. Hence new entries are no direct competition and do therefore not influence the price negatively. Thus I reject hypothesis 2a.

Hypothesis 2b: the price of cryptocurrencies is negatively influenced by substitutes.
Hypothesis 2b is rejected for all individual cryptocurrencies. This is mainly caused by a lack of significant relationships. The weekly data on the other hand shows that cryptocurrency prices are negatively influenced by S&P500. Indicating that cryptocurrencies might be vulnerable to substitutes. This is in line with previous research of Hong who claimed that cryptocurrency price movements are contrary to the price movements of traditional investments. This finding is at a 99% significance level. Hence, I accept hypothesis 2b for ordinary years.

Hypothesis 3a: the price of cryptocurrencies is influenced by public interest.
Public interest has an significant influence on the price movement Ripple and Ethereum. The price movement of Litecoin and Bitcoin on the other hand is not significantly influenced by *public interest*. I rejected the hypothesis for NEM due to non-significant results. Ripple and Ethereum are relative new cryptocurrencies compared to Litecoin and Bitcoin. Their maturity might cause the fact that Litecoin's and Bitcoin's price movement is unaffected by *public interest*. These currencies do also differ in block time, but this seems not a likely explanation as most investors are not aware of the technical characteristics of each cryptocurrency (Pakrou & Amir, 2016).

Hypothesis 3b: the price of cryptocurrencies is negatively influenced by regulatory attention.
Regulatory attention shows insignificant relationships across all years. I therefore reject hypothesis 3b.

Hypothesis 3c: the price of cryptocurrencies is negatively influenced by negative related attention.
Negative attention shows insignificant relationships during 2016 for both Ripple and the weekly data. I therefore accept hypothesis 3b for normal years. During 2017 on the other hand *negative attention* does show significant relationships with price movement. Against expectations a positive relationship with price movement can be recognized in 2017. Which should, as per theory, have a negative impact on cryptocurrency's prices. I therefore reject hypothesis 3b. Wang and Vergne (2017) came to a similar conclusion and state that the type of attention is irrelevant during the current growth stage. Again this might indicate that there were different forces influencing 2017's price level, for example the progress to maturity. Suggesting that the urge to grow was stronger than the influence of regulatory related attention. Another explanation can be that any type of attention, negative or positive, acted as an catalyst for unwitting people to buy cryptocurrency. Further research can reveal if this remains the same when the cryptocurrencies mature.

*Table 5.6: weekly cryptocurrency regression table. Weekly return cryptocurrency as dependent variable. Whereas the numbers not in parentheses are the standardized betas and the numbers within parentheses is the standard error. Significance is denoted with * p<0.10. ** p<0.05. ***p<0.01. Model 1 is cost-based, model 2 is supply and demand, model 3 is technical analysis and model 4 includes all variables.*

	2016				***2017***				***2016-2017***			
Model	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Variable												
daily return U.S.	.154			.218	-.071			-.030	.041			.099
commodity index	(.907)			(.859)	(2.068)			(1.832)	(.962)			(.828)
daily return S&P500	-.359**			-.338**	-.013			.011	-.180*			-.163*
	(.967)			(.912)	(2.026)			(1.773)	(1.009)			(.870)
negative attention	-.160			-.134	.595***			.624***	.322***			0.576***
	(.004)			(.003)	(.001)			(.001)	(.000)			(.001)
coal price		-.295		-.397*		-0.015		-.279		-.067		-.430
		(.002)		(.002)		(0.009)		(.005)		(.001)		(.001)
liquidity growth			.375***	.314**			.464***	.384***			.421***	.370***
cryptocurrency			(.019)	(.018)			(.022)	(.021)			(.015)	(.014)
supply growth	.118		.088	.056	.236*		.273**	.290**	0.278***		.165*	.207**
cryptocurrency	(18.889)		(18.590)	(18.095)	(23.339)		(21.999)	(20.310)	(15.574)		(14.131)	(13.471)
exchange rate	-.149	-.007	-.204	.222	.487**	0.382	.091	.280	.144	.125	.103	.424***
Chinese Yen	(.093)	(.174)	(.088)	(.163)	(.174)	(0.714)	(.131)	(.193)	(.073)	(.085)	(.071)	(.088)
Number of observations	260	258	233	231	260	258	260	258	520	516	493	489
Adjusted R2	.231	.090	.234	.383	.272	.035	.338	.502	0.164	.012	.234	.361
Durbin Watson	1.936	2.212	2.360	2.101	1.569	1.469	1.511	1.753	1.648	1.532	1.553	1.941

Hypothesis 4a: the price of cryptocurrencies is influenced by volume.

All included altcoins are positively influenced by volume. Suggesting that a high volume always indicates higher price levels (which is against the theory of Blume, et. al (1994)). The correlation beta's become larger and more significant during 2017 for al Altcoins. This positive relationship is the strongest for Ripple since Ripple yields the highest betas (.471 and .465 in 2017). Which can easily be explained as Ripple's price increased most during 2017 (35048%). Thus I accept hypothesis 4a for all Altcoins. Bitcoin on the other hand shows no significant relationships, this absence can be explained by the loss of Bitcoin's market share during 2017 (as can be seen in appendix 9.1). Hence, I reject hypothesis 4a for Bitcoin.

Hypothesis 4b: the price of cryptocurrencies is positively influenced by scarcity.

This hypothesis is tested on all included cryptocurrencies except from NEM. However, the effect of scarcity was not significant when regressing it on individual cryptocurrencies. Additionally scarcity shows positive relationships with the accumulated cryptocurrencies during 2017 (although subject to autocorrelation). This indicates that a larger supply increases the price, which is not in line with the theory. I therefore reject hypothesis 4b due to both insignificant and positive relationships.

6 CONCLUSION

The starting point of this research was a lack of available research and no clear consensus regarding the price movement of cryptocurrencies. Hence, this research aimed to find out what factors have explanatory power regarding cryptocurrencies price movement. Additionally, the applicability of some longstanding theories in regards to cryptocurrencies price movement is tested. Both sub questions help to answer the central research question: How can the price movement of cryptocurrencies be explained?

What factors can explain the price movement of cryptocurrencies?

Volume is the factor that has most explanatory power for altcoins. This factor shows significant relationships during the overall period and 2017, but volume shows less often significant relationships during 2016. The relationships between volume and price movement often are positively correlated, which makes it questionable if these results will hold in the future when the altcoins mature. Bitcoin, the most mature cryptocurrency, on the other hand shows no significant relationships with volume or any other factor. This might be due to the fact that daily data analysis results in noisy results. However, overall volume can be seen as the factor with most explanatory power. Additionally, public interest and any type of attention prove to be valuable predictors for most currencies during the year of rapid growth for Ripple and for the average weekly data. These factors do have explanatory power despite the fact that negative or regulatory attention did not have the expected negative influence. Most results of cryptocurrencies contradict previous theories. For example, Ripple is negatively influenced by a growing public trend in 2016, while it is positively influenced by negative attention in 2017. Lastly the S&P500 moves, during ordinary years, has a negative influence on price movement of cryptocurrency.

What pricing theories can be applied to cryptocurrencies?

Three pricing theories are converted to a model and tested in regards to five cryptocurrencies. All models have, compared to previous studies, low explanatory power. The highest adjusted R squared value of this research is .274 (model 3, during 2017 for the unweighted average of cryptocurrencies). Models by Luchansky and Monks (2009) and Bettman et al. (2009) yield adjusted R squared values of .638 and .755. The fact that the models regarding cryptocurrency yield low R squared values regarding cryptocurrencies is in line with Chatterjee et al. (2017) who stated that there is no scientific model with enough scientific power to explain the price movements of cryptocurrencies. This finding indicates that the currently tested pricing theories cannot be applied to cryptocurrencies. Nevertheless, some results offer a valuable start for further research. Namely, a clear difference between an ordinary year and a year of rapid growth can be seen. Whereas technical analysis shows the highest explanatory power, during a year of high growth, supply and demand the second best results, but mainly during a normal year. Additionally, most hypotheses and theories seemed more applicable in 2016 compared to 2017. These results show that 2017 might not be a relevant year for research purposes. Unless it concerns technical analysis related research towards extreme cases, such as Ripple (35048% increase) or NEM (29173% increase). The cost price related model shows the least explanatory power among all models. However, some results of 2016 are in line with the theory. Thus, the pricing theory that has most explanatory power in regards to cryptocurrencies is technical analysis. However, its explanatory power is mainly due to the explanatory power of volume in 2017. Hence, further research must point out if this finding holds. Additionally, more research towards ordinary years, with different (more reliable variables – see section 7.1) must show if supply and demand theory can be more explanative.

What can the price movement of cryptocurrencies explain?

Given the answers to previous question it seems difficult to explain how the price movement will evolve in the future. Different factors and models bear different p values or adjusted R squared values, hence explanatory power. Currently technical analysis seems to yield the best results. However, this is mainly due to its explanatory power during years of high growth. Supply and demand based proves to have a similar explanatory power during 'normal' years. I therefore agree with Taylor and Allen (1992) who suggest to use both fundamental (supply and demand in this case) and technical analysis aspects in order to explain price movement.

Furthermore cryptocurrencies price movement can be better explained over a longer period of time since weekly data showed higher adjusted R squared values than daily data. Additionally more significant relationships (that were in line with the theory) were due when testing the weekly data. Indicating that daily data is noisy, or worse, biased. Hence, daily data proved to be too noisy to provide a proper explanation and prediction. Perhaps longer periods of time result in even more explanatory power. This finding questions the results Ciaian, et al. (2016) who claimed that cryptocurrency was better explainable on the short run than on the long run. Further research must point out whether their research is biased or outdated given the rapid changes cryptocurrencies endure. Especially when taking into account that cryptocurrencies price movement is subject to different phases in their development, each with different characteristics which might bias the data. I therefore fully agree with Chatterjee, et al. (2017, p. 16) who state: "*On the whole, we simply do not have a scientific model with sufficient predictive power to answer questions about how Bitcoin or related systems [altcoins] might fare with different parameters or in different circumstances. (…) Bitcoin is a rare case where practice seems to be ahead of theory.*".

7 DISCUSSION

Cryptocurrency and their price movement are part of a new and still emerging field of research. Rapid changes and new findings occur on a regular bases. As a result of these changes and other restricting circumstances this report will have some limitations, these are described in section 7.1. Additionally, some unanswered questions that raised during the conduction of this report can be valuable suggestions for further research. These are repeated and further elaborated upon in paragraph 7.2.

7.1 LIMITATIONS

First of all, some compromises are made regarding the data. Mainly financial data, for example coal prices, natural gas prices or commodity indexes, were not freely available. Resulting in the adoption of less accurate data sources. For example the U.S. commodity index is used instead of a global commodity index. Additionally, trends.google.com for instance solely provides percentages based on the peak period. Due to large changes the peak period is, obviously, 100%, while most other periods are below 10 or even 0.

Secondly, the Augmented Dickey Fuller Test (ADF) is not performed due to a limitation of the SPSS software. In previous research by Ciaian, et al. (2016) and Wang and Vergne (2017) the ADF is performed to assess whether there is stationarity. Montgomery et al. (2001) state that the time series analysis must be checked for non-stationarity, otherwise the data may lead to spurious results. Montgomery et al. (2001) also state that the ADF is more applicable to time series than an ordinary Dickey Fuller Test, but both tests assess whether a unit-root is present. However, SPSS did not provide either of these tests.

Furthermore, this research is solely focussed on successful cryptocurrencies (top 5), their performance might be different compared to ‘ordinary’ cryptocurrencies. Additionally, solely two years of data is available for these currencies. Although this lack of observations did not influence the statistical power, it ruled out observations from the start of 2016. Possibly changing the explanatory power. Further research towards ‘older’ and less successful cryptocurrencies might result in different insights.

Finally, multiple limitations are not remedied due to time restrictions. For example, only one variable is used to measure the influence of cost-based. This strong correlation has a great impact on explanatory power and robustness of model 2 (cost-based model), since only one variable can be used simultaneously. Resulting in only one variable to test the model, which is seen as a limitation for this research. Adopting and including new (not correlating) measurement instrument would cost a significant amount of time. I leave this open for further research. Additionally due to the absence of the daily statistics of Ciaian, et al. (2016) it is difficult to benchmark most of the daily data. As well as, unscaled data, such as *exchange rate Euro*, *natural gas price* and *public interest,* is not discussed due to a lack of benchmarking possibilities. This makes it difficult to assess the reliability of this research. Other, similar benchmark methods, such as similar exchange rates or commodity prices are not investigated due to time limitations.

7.2 FURTHER RESEARCH

Throughout the report some topics for further research are given. This section includes all those topics and additions. The first suggestion for further research is a repetitive study containing different, less biased, data input. Furthermore the time period of two years is rather short given the outcomes that are not in line with longstanding theories. Additionally, multiple other cryptocurrencies (not top 5) can be included to see how they perform.

Secondly, within this research the question arose if one cryptocurrency is superior to another. However, no distinct differences are retrieved from the current data set. Which is not in line with the theory. This provides room for further research with more currencies to maintain statistical power. Moreover, if this superiority is correlated by reoccurring characteristics.

As third, the effect of the blockchain authorization is investigated in this research. However, little statistically significant data was retrieved. Whether this is due to a compromises made in data collection, measurement error or simple because there is no significant relation remains unclear up to this moment. Yet, Bitcoin showed results that are in line with theories and expectations. Therefore I suggest that further research can be done to assess the influence (on price) of cryptocurrencies' blockchain authority. For example by including multiple cryptocurrencies or different models.

Fourthly, the relationship between volume and price movement is predominantly positive for all cryptocurrencies throughout this report. This is absolutely not in line with prior scientific research. Hence, repetitive research (including a longer sample period) must show if this finding holds.

Finally, a rather technical topic for further research was proposed by Hayes. He recognized the vast amount of energy that cryptocurrencies consume currently. Hayes proposed further research to this consummation. Both to the financial and ecological effects. For example, how can blockchains become less energy consuming, but still safe to use. Reducing the carbon footprint of cryptocurrencies.

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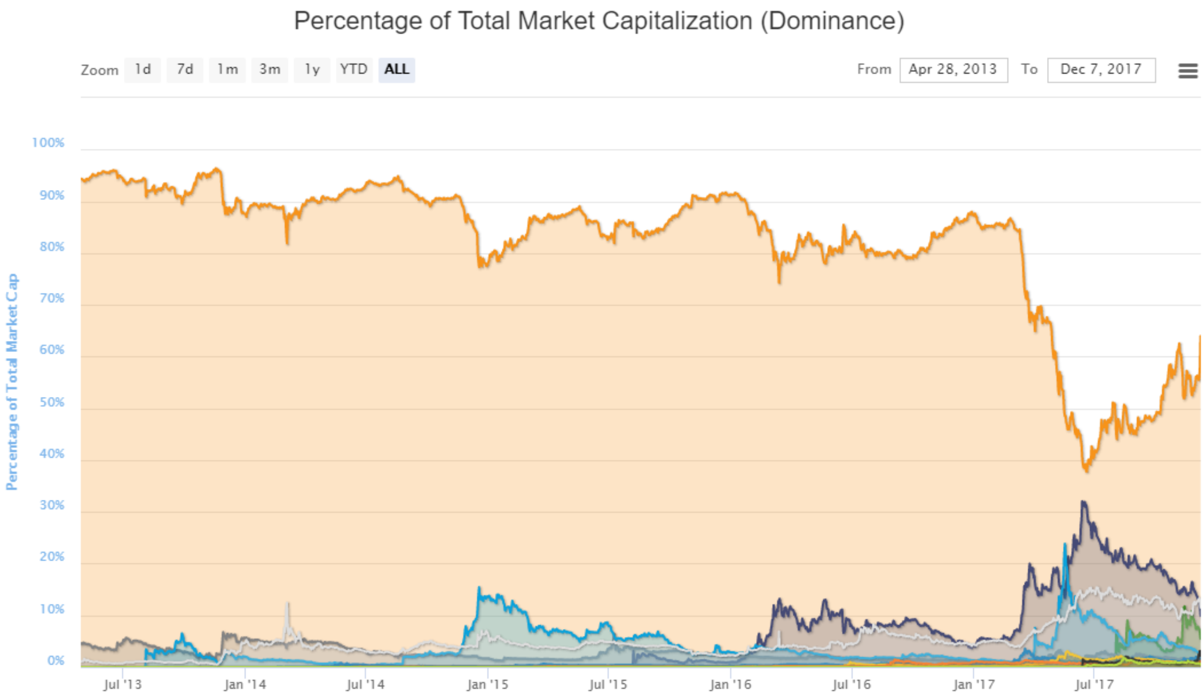
9 APPENDIX

9.1 HISTORICAL MARKET CAPITALIZATION CRYPTOCURRENCY



Source: https://coinmarketcap.com/charts/ (7th of December, 2017)

9.2 SOURCE MATRIX

Tabel 6.1 source matrix. Sorted on search query (A-Z).

Author, article & year	Search query	Source	Method	Main consensus	Limitations
Janiszewski (How to perform discounted cash flow valuation?, 2011)	"discounted cash flow"	Foundations of Management	Review	The Discounted Cash Flow valuation reflects the ability of the company to generate cash in future. Factors such as tax rate, discount rate, WACC influence the outcome of DCF valuations. DCF valuation also is used to present optimistic, pessimistic and realistic scenarios based on different set of assumption. "cash flows that are available to all providers of the company's capital, both creditors and shareholders, after covering capital expenditures and working capital needs"	No empirical data, little use of other sources. Mainly reasoning. Solely focussed on companies.
French (The discounted cash flow model for property valuations: quarterly cash flows, 2013)	"discounted cash flow"	Journal of Property Investment & Finance	Review	DCF valuation involves projecting estimated cash flows over an assumed holding period, plus an exit value at the end of that period, usually arrived at on a conventional all-risk yield (ARY) basis (exit yield). The cash flow is then discounted back to the present day at a discount rate that reflects the perceived level of risk.	Mainly focussed on company valuation.
Kaplan & Ruback (The Valuation of Cash Flow Forecasts: An Empirical Analysis, 1995)	"discounted cash flow"	Journal of Finance	Regressions	" Our median estimates of discounted cash flows for 51 HLTs are within 10 percent of the market values"	Small number of observations (51).
Lundholm & O'Keefe (Reconciling Value Estimates from the Discounted Cash Flow Model and the Residual Income Model, 2001)	"discounted cash flow"	Contemporary Accounting Research	Regressions	Research towards the difference and explanatory power of multiple valuation techniques. Reveals that no technique is superior to another. Differences are usually caused by flaws in the forecast. "Research efforts in valuation would be better spent on the study of how to make more accurate forecasts of financial statement data, not in how to represent and discount the resulting flows of value"	

Armitage (Incorporating financing-related determinants of value in the discounted cash flow model, 2008)	"discounted cash flow"	Journal of Economic Surveys	Review	Provides a list with all types of factors that are indirectly represented (incorporated) in the DCF.	Solely based on reasoning and previous research. No own empirical evidence.
Berry, Levinsohn, & Pakes (Automobile Prices in Market Equilibrium, 1995)	"supply and demand" AND/OR "demand and supply"	Econometrica	Logit regression	Research towards price automobiles. Suggest that demand is caused by level of utility a product delivers to potential owner. Level of utility consists of buyer characteristics and product characteristics. 61.3% of utility is described by unobservable characteristics. However, observable characteristics are able to explain price by R2 0.66. Elasticity calculated by delta % quantity/delta % price.	
Dierker, Kim, Lee & Morck (Investors' Interacting Demand and Supply Curves for Common Stocks, 2016)	"supply and demand" AND/OR "demand and supply"	Review of Finance		A stock's fluctuating market price and investors' fluctuating heterogeneous private valuations can move investors from the buy-side to the sell-side and vice versa, thus shifting their weight from one elasticity to the other The stock market is a pure exchange economy - thus subject to supply and demand. Elasticity calculated by delta % quantity/delta % price.	
Kraus & Stoll (Price Impacts of Block Trading on the New York Stock Exchange, 1972)	"supply and demand" AND/OR "demand and supply" -> snowball method		Cross sectional analysis	Influence of block trades on market efficiency. Stock prices are subject to supply and demand primarily. However, other costs, such as the costs of institutions influence stock prices as well.	
Luchansky & Monks (Supply and demand elasticities in the U.S. ethanol fuel market, 2009)	"supply and demand" OR "demand and supply"	Energy Economics		substitute for ethanol (gasoline) influences price. Cheaper gasoline decreases demand ethanol. Change quantity/change formula used to calculate elasticity. Created a model including external factors to predict price, model has high explanatory power (R2 0.638).	

Chatterjee, Son, Ghatak, Kumar & Kharie (BitCoin exclusively informational money: a valuable review from 2010 to 2017, 2017)	Bitcoin	Quality and Quantity	Literature survey	There is no scientific model with sufficient predictive power to answer questions about how Bitcoin or related systems might fare with different parameters or in different circumstances. Characteristics: decentralized, peer-to-peer, cheaper, anonymous, cross border, quicker.	No own empirical data
Tan & Low (Bitcoin – Its Economics for Financial Reporting, 2017)	Bitcoin AND currency AND commodity	Australian Accounting Review	Review	According to theory: commodity. However, it can differ per type of user. Basic distinction: trader vs. wallet. Fiat money is status quo of currencies	No empirical data, little use of other sources. Mainly reasoning.
Ciaian, Rajcaniova & Kancs (The economics of BitCoin price formation, 2016)	Bitcoin AND Price	Applied Economics	Time series analysis, macro financial factors and market forces	Market forces and BitCoin attractiveness for investors and users have a significant impact on BitCoin price but with variation over time. Our estimates do not support previous findings that macro financial developments are driving BitCoin price in the long run. Cryptocurrencies are decentralized, peer-to-peer, cheaper, anonymous, cross border.	Solely focussed on Bitcoin; Data 2009-2015
Blau (Price dynamics and speculative trading in Bitcoin, 2018)	Bitcoin AND Price	Research in International Business and Finance	Regression, time series	Recognizes bubbles, but no signs of speculative trading are seen. Characteristics: decentralized, peer-to-peer, cheaper, anonymous, quicker. Until 2014 no significant speculative trading.	
Hong (Bitcoin as an alternative investment vehicle, 2017)	Bitcoin AND price	Information Technology Management	Regression	Adding Bitcoin to a traditional portfolio is beneficial for institutional investors. A significant time series momentum is found. Characteristics: Decentralized, peer-to-peer, cheaper, quicker. Transaction fees, there is speculative trading.	Solely focussed on TSM; Data includes bubbles
Hayes (Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin, 2017)	Bitcoin AND Value	Telematics and Informatics	Regression	Cost price is mainly caused by energy price (for mining). Costs/benefit ratio decreases when price increases. Characteristics: un- and under-banked, decentralized, peer-to-peer, cheaper, anonymous. Model created based on costs, no other factors taken into account.	Solely focussed on costs; Non-economic article
Noble & Gruca	Cost-based pricing	Marketing Science	Survey	We establish the price of the product at a point that gives us a specified percentage profit margin over our costs.	

(Industrial Pricing: Theory and Managerial Practice, 1999)					
Franklin Jr. & Diallo (Valuing Real Options for Network Investment Decisions and Cost-Based Access Pricing, 2012)	Cost-based pricing	The Engineering Economist	Time-series analysis	Cost-based prices are subject to several factors, such as new entry costs or economies of scale/scope (described as joint and common costs), demand uncertainties etc.	Mainly regarding valuing real options, little in-depth information regarding cost-based
Hove (Cost-based pricing of payment instruments: the state of the debate, 2004)	Cost-based pricing	De Economist	Review	Not description of the theory is given, but speaks only about authorities and managers who determine prices of (payment) services. Explains why cost-based pricing is inefficient and unfair.	No own empirical data
Hinterhuber (Value First then Price: Quantifying value in Business to Business markets from the perspective of both buyers and sellers, 2016)	Cost-based pricing AND/OR Pricing	University Library		The cost-based pricing theory determines the actual value based upon the cost price and a certain premium.	Aimed at firm pricing rather than stock or currency pricing.
Cheung, Roca & Su (Crypto-currency bubbles: an application of the Phillips-Shi-Yu (2013) methodology on Mt. Gox bitcoin prices, 2015)	Cryptocurrency	Applied Economics	Time series (Phillips, et al. (2013) procedure)	A few short-lived bubbles and three huge bubbles have been detected. There are little to no cash flows, little is known about Bitcoin's nature. No characteristics explained, until 2014 no significant speculative trading.	Solely focussed on Bitcoin; Data 2010-2014
Wang & Vergne (Buzz Factor or Innovation Potential: What, 2017)	Cryptocurrency AND currency AND commodity	PLoS ONE	Regression	Cryptocurrencies can have various implications (e.g., payments, smart contracts, record keeping), each of which can create a certain amount of value. Strictly cryptocurrencies are nor commodity nor currency. Rather a commodity than currency. Strictly none. Cryptocurrencies contain valuable technology that can be improved (not a characteristic of currency or commodity). Claim for “synthetic commodity money”, but technical purposes need to be investigated.	Focusses on returns rather than price formation. Solely regarding Bitcoin and 4 Altcoins (no comparison made among them)

Pakrou & Amir (The Relationship between Perceived Value and the Intention of Using Bitcoin, 2016)	Cryptocurrency AND value	Journal of Internet Banking and Commerce	Factor analysis and SEM	Perceived value, infrastructural, individual and cultural factors are positively correlated to the intention to use Bitcoin. There is no correlation between political and environmental factors to the use of Bitcoin.	Inaccessibility to the Bitcoin's users. Statement of being non-concentrated not supported.
Bollen & Rasiel (The performance of alternative valuation models in the OTC currency options market, 2003)	Currency AND valuation	Journal of International Money and Finance	Time series analysis	Mainly regarding option valuation. Few statements regarding currency valuation. They compare several models but "Neither model, however, permits discontinuities in the evolution of exchange rates."	Mainly focussed on option pricing/valuation. Little said about currency valuation
Vlaar (GDP growth and currency valuation: The case of the dollar, 2007)	Currency AND valuation	Journal of International Money and Finance	Time series analysis, regression	Empirical evidence that country growth influences currency price. Other influential factors: wealth, inflation.	Uses his own designed model
Leach & Melicher (Entrepreneurial Finance, 2015)	None	Prescribed literature		An estimate of the future cash flows ant the risk rate (discount rate) are needed to calculate the value expected value via the discounted cash flow method - project financial statements	Aimed at firm pricing rather than stock or currency pricing.
Hillier, Grinblatt, & Titman (Financial Markets and Corporate Strategy, 2012)	None	Prescribed literature		An estimate of the future cash flows and the risk rate (discount rate) are needed to calculate the value expected value via the discounted cash flow method	Aimed at repaying equity holders rather than pricing stock/currency.
Kotler, Wong, Saunders & Armstrong (Principles of Marketing, 2005)	None	University Library		Cost-based pricing theory determines the actual value based upon the cost price and a certain profit margin. Difference between fixed and variable, two together form lower price limit, while market demand forms the upper limit. Price increases when scarce, firms usually fill this gap.	Marketing principles instead of financial principles, more aimed to product pricing.
Porter (The five competitive forces that shape strategy, 2008)	None	Harvard Business Review		Substitutes are competition, therefore prices need to be more competitive. Usually this results in lower prices.	Marketing principles instead of financial principles, more aimed to product pricing.

Marshall (Principles of Economics, 1890)	Principles of Economics – snowball technique	University Library		Supply and demand are two separate curves which can be combined - an equilibrium is reached where lines intersect. Curves are influenced by buyer and supplier characteristics. Cost of carriage and scarcity do also influence demand.	Outdated at some points - for example cost of carriage is neglectable within the UK nowadays.
Vali (Principles of mathematical economics, 2014)	Principles of Economics	University Library		Supply and demand are two separate curves which can be combined - an equilibrium is reached where lines intersect. Curves are influenced by buyer, such as income and supplier characteristics, such production costs.	
Rogoff (The Purchasing Power Parity Puzzle, 1996)	Purchasing Power Parity	Journal of Economic Literature		Difficulties regarding volatility, it would seem hard to explain the short-term volatility without a dominant role for shocks to money and financial market	Relatively old article, but recited and recognized in 2004.
Taylor & Taylor (The Purchasing Power Parity Debate, 2004)	Purchasing Power Parity	American Economic Association	Cointegration regression	Definition: the nominal exchange rate between two currencies should be equal to the ratio of aggregate price levels between the two countries, so that a unit of currency of one country will have the same purchasing power in a foreign country. Difference between absolute PPP and relative PPP. Short-run PPP does not hold, long-run PPP may hold in the sense that there is significant mean reversion of the real exchange rate, although there may be factors impinging on the equilibrium real exchange rate through time.	
Aoki (An empirical analysis on the law of purchasing power parity and international economic deepening, 2013)	Purchasing Power Parity	Applied Economics	Linear regression	Tested the deviation from law of PPP based upon several influencers such as; wage rate, consumer price index, nominal interest rate, exchange rate per US dollar and money supply (per-population). These influencer have more explanatory power for developed countries (R2 of 0.4181-0.6757 vs. 0.1787-0.3688)	Limited amount of observed countries (7).

Bahmani-Oskooee (Purchasing Power Parity Based on Effective Exchange Rate and Cointegration: 25 LDCs' Experience with its Absolute Formulation, 1993)	Purchasing Power Parity	World Development	Cointegrati on regression	In its absolute form, the purchasing power parity (PPP) theory asserts that the exchange value of a country's currency is determined by the ratio of the domestic to the foreign price level. R;, = PjP, and P, = R, x P,	Relatively old article, but recited and recognized in 1996.
Hoque (A test of the purchasing power parity hypothesis, 1995)	Purchasing Power Parity	Applied Economics	Cointegrati on regression	A cointegrated system allows individual time series to be integrated of order one (that is, 1(1)), but requires a linear combination of the series to be stationary (that is, 1(0)), the PPP is testable using the theory of cointegrated process. Values determined between 1961 and 1990.	Solely focussed on non-developed countries (only 4).
Kettell (Economics for Financial Markets: A volume in Quantitative Finance, 2002)	Supply and demand	University Library		Price increases when scarcity exists. Currency-wise this gap balances itself due to market demand factors (eventually equilibrium): "the value of transactions would (…), money back together".	
(Taylor & Allen, 1992, p. 304).	"technical analysis"	Journal of International Money and Finance	Survey	"Technical, or chart, analysis of financial markets involves providing forecasts or trading advice on the basis of largely visual inspection of past prices, without regard to any underlying economic or 'fundamental' analysis" TA is more used to predict short term behaviour, fundamental analysis for long term. In some cases a combination is used.	
(Blume, Easley, & O'Hara, 1994, p. 151)	"technical analysis"	The Journal of Finance	Equilibrium model	"Technical analysts believe that price and volume data provide indicators of future price movements, and that by examining these data, information may be extracted on the fundamentals driving return."– scepticism regarding TA - volume is an explanatory factor, see graphs and formula's.	

(Neely, Weller, & Dittmar, 1997, p. 406)	“technical analysis”	Journal of Financial and Quantitative Analysis	random walk, ARMA, and ARMA-GARCH models.	The technical approach to investment is essentially a reflection of the idea that prices move in trends which are determined by the changing attitudes of investors toward a variety of economic, monetary, political and psychological forces... Since the technical approach is based on the theory that the price is a reflection of mass psychology ("the crowd") in action, it attempts to forecast future price movements on the assumption that crowd psychology moves between panic, fear, and pessimism on one hand and confidence, excessive optimism, and greed on the other.	
(Lo, Mamaysky, & Wang, 2000, p. 1706)	“technical analysis”	Journal of Finance	Kernel regression	“These linguistic barriers underscore an important difference between technical analysis and quantitative finance: technical analysis is primarily visual, whereas quantitative finance is primarily algebraic and numerical.” - scepticism regarding TA – provide formula for TA. Outcomes of the formula must be smoothed to be able to estimate nonlinear relations. When using Kernel regression bandwidth is of importance.	

9.3 MARKET CAPITALIZATION 01-01-2015 UNTIL 31-12-2017

Retrieved from Coinmarketcap.com/charts on January 11, 2018. Whereas the squared part presents the period of rise and the other part the 'normal' year before.

9.4 EXCLUDED DAYS DATA COLLECTION

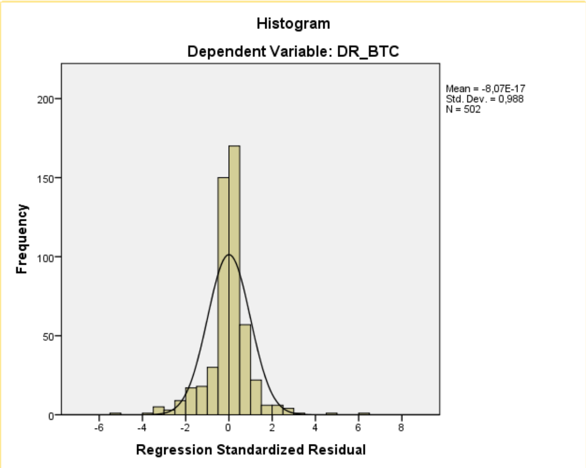
2016	**2017**	**Reason**
Monday January 1st	Monday January 2nd	New Year's Day
Monday January 18th	Monday January 16th	Bank holiday
Monday February 15th	Monday February 20th	Bank holiday
Friday March 25th	Friday April 14th	Good Friday
Monday May 30th	Monday May 29th	Spring bank holiday
Monday July 4th	Tuesday July 4th	4th of July
Monday September 5th	Monday September 4th	Bank holiday
Thursday November 24th	Thursday November 23rd	Thanksgiving
	Monday December 25th	Christmas day
Monday December 26th	Tuesday December 26th	Boxing day

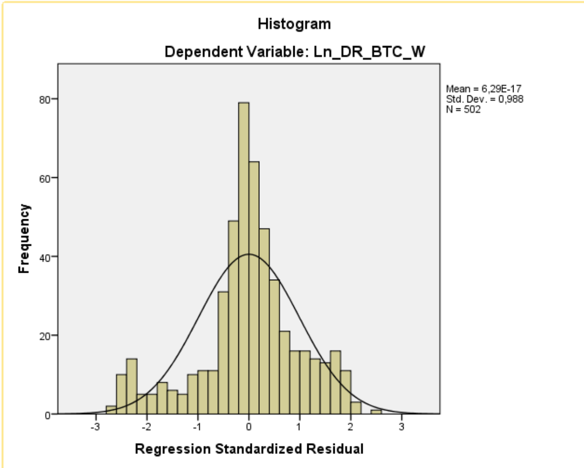
9.5 Data before and after corrective measures

Normality of the residuals' distribution

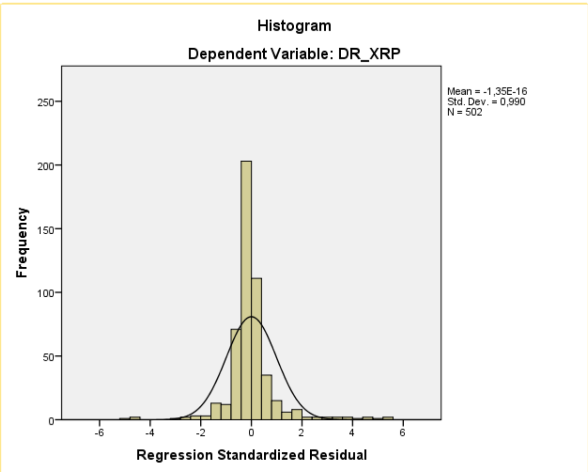
Histograms of multiple regression analysis with daily return$_i$ as dependent variable and exchange euro, public interest, daily return S&P500, daily return U.S. commodity index, liquidity growth$_i$, supply growth$_i$, prior return$_i$ and number of currencies. Outcomes before corrective measures left (subject to kurtosis) and after corrective measures right (normally distributed).

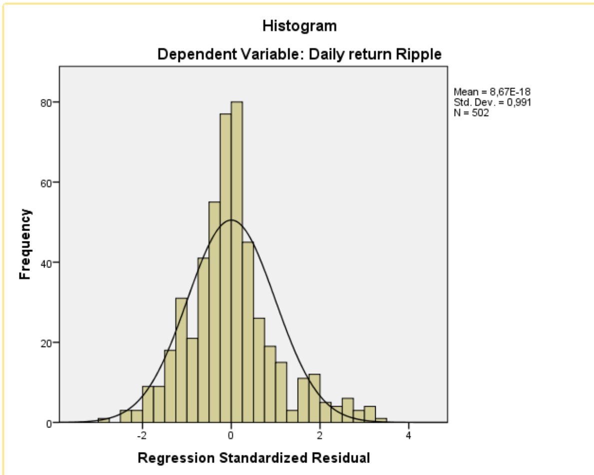
<u>Bitcoin</u>



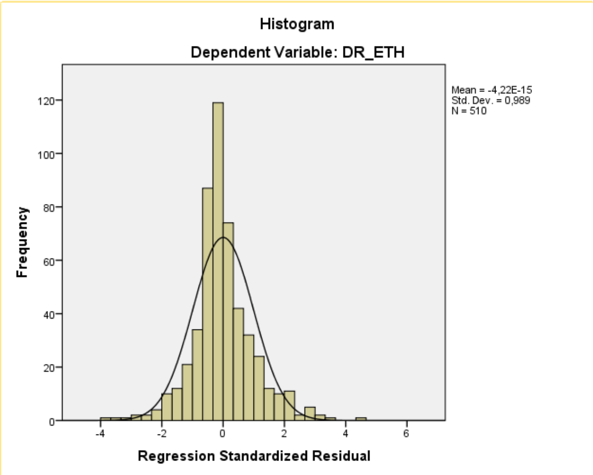


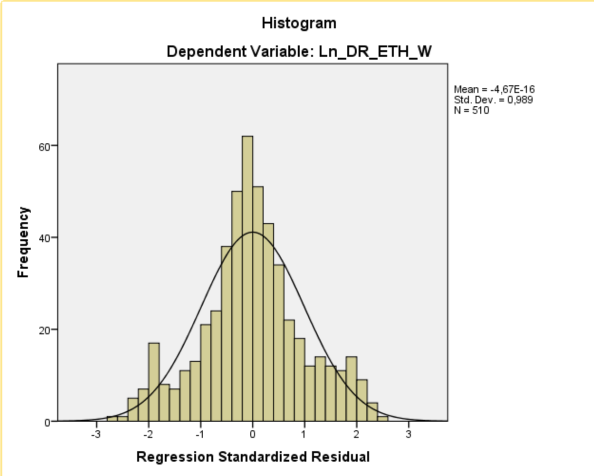
<u>Ripple</u>



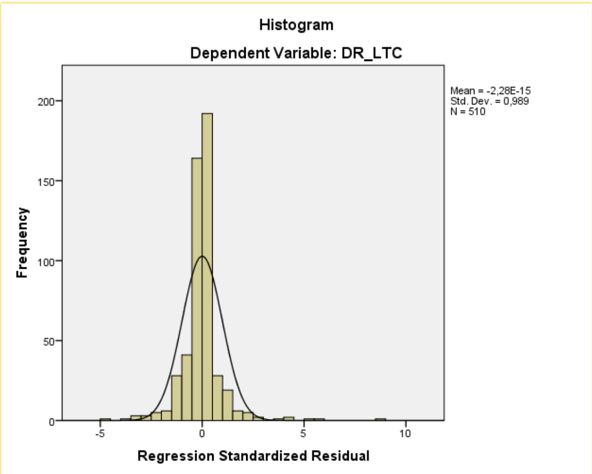


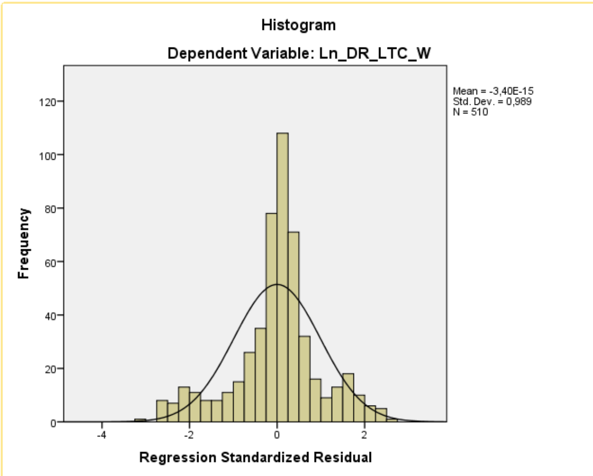
Ethereum



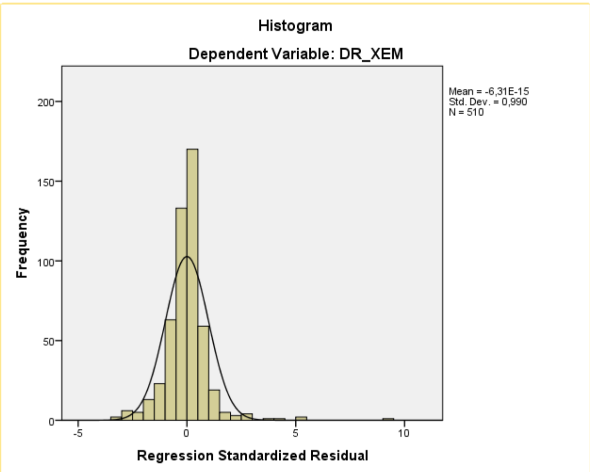


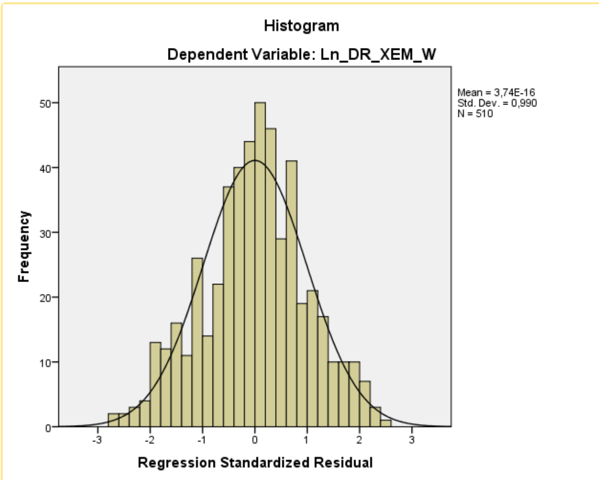
Litecoin





XEM

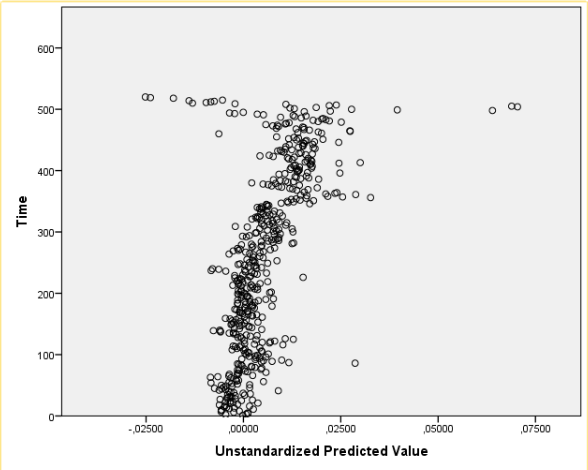


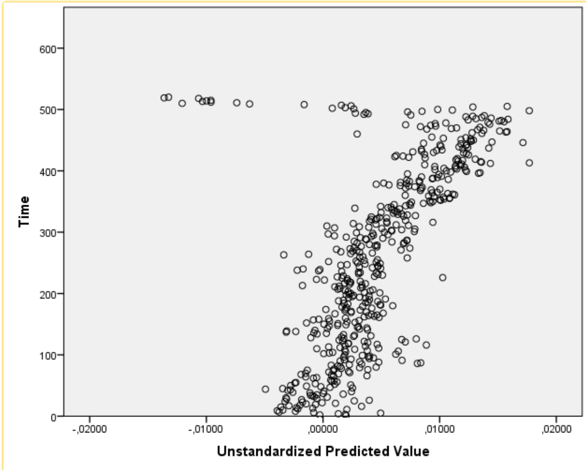


Constant variance of the residuals

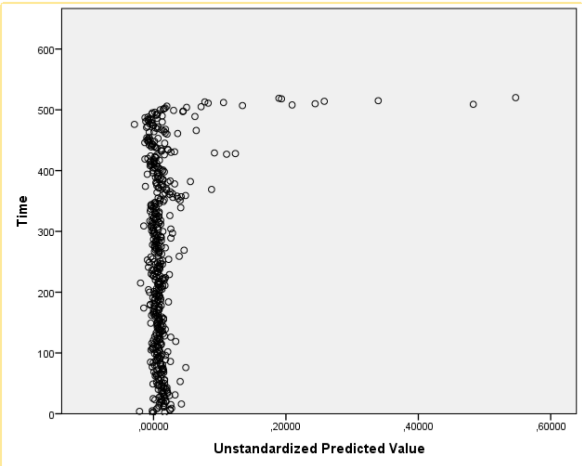
Unstandardized residuals multiple regression analysis versus time plot. With daily return Ripple as dependent variable and exchange euro, public interest, daily return S&P500, daily return U.S. commodity index, liquidity Ripple, current supply Ripple and number of currencies. Outcomes before corrective measures left (Durbin Watson value of 2.014) and after corrective measures right (Durbin Watson value of 1.870).

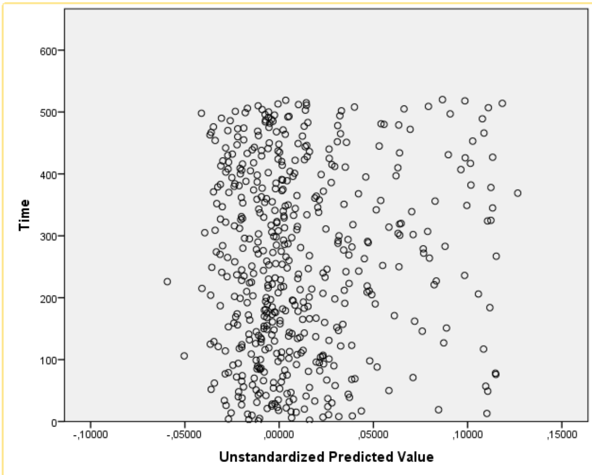
Bitcoin



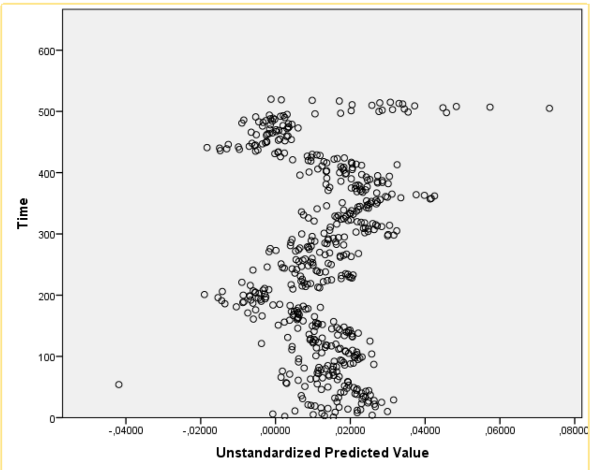


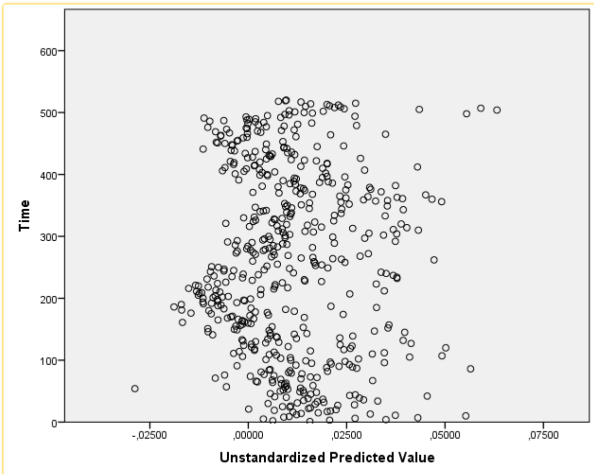
Ripple



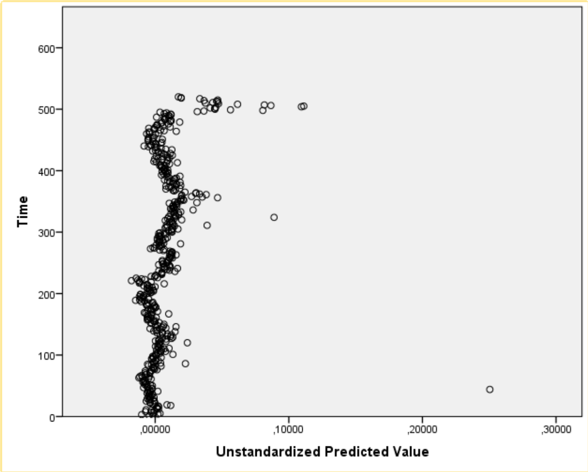


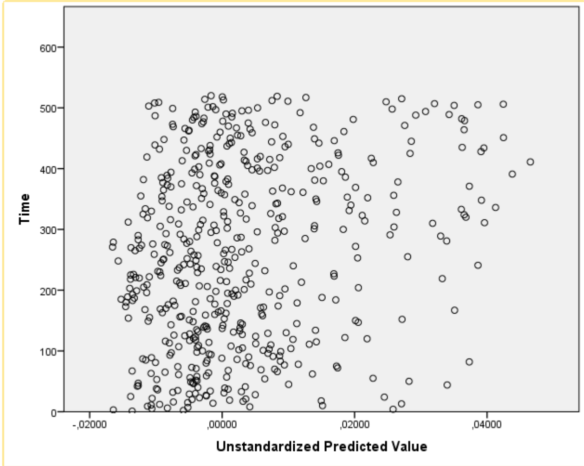
Ethereum



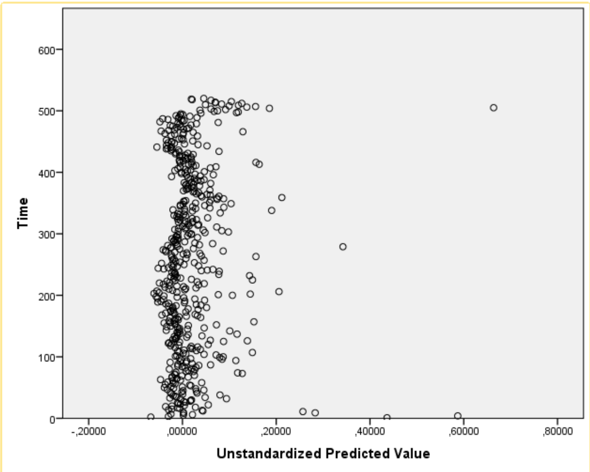


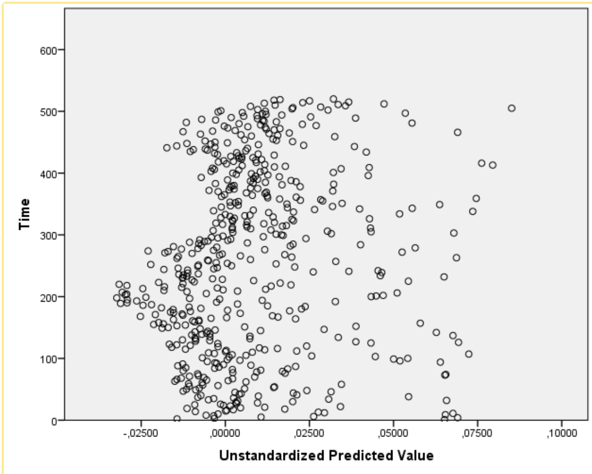
Litecoin





NEM

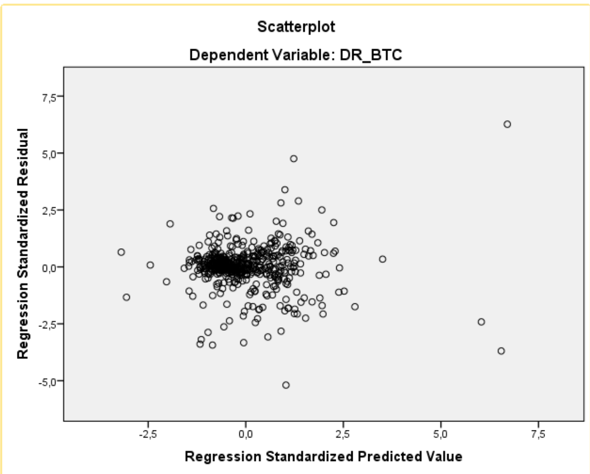


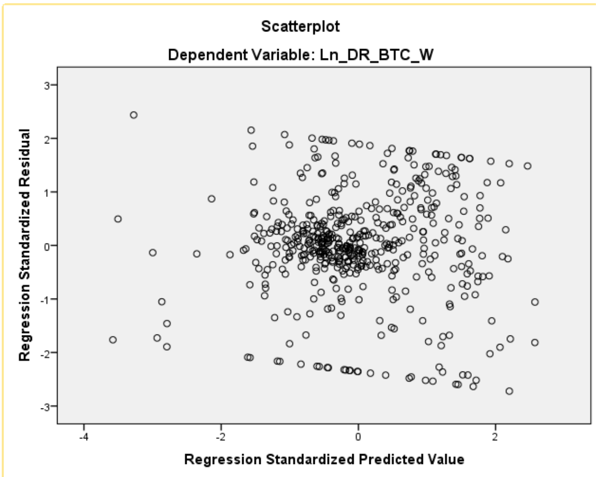


Independence of the residuals

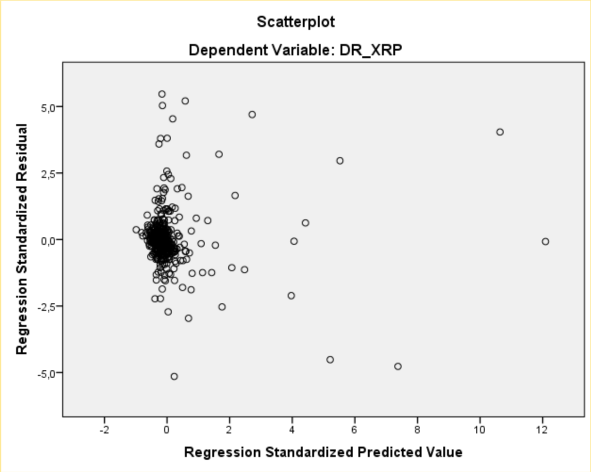
Standardized residuals multiple regression analysis versus standardized predicted value. With daily return Ripple as dependent variable and exchange euro, public interest, daily return S&P500, daily return U.S. commodity index, liquidity Ripple, current supply Ripple and number of currencies. Outcomes before corrective measures left (clustered and cone-shaped) and after corrective measures right (rectangular).

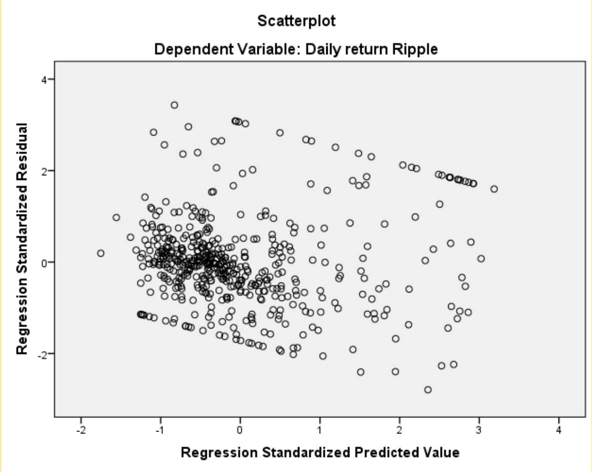
Bitcoin



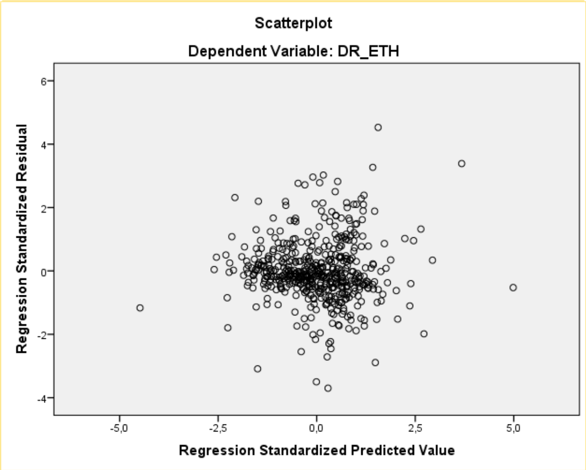


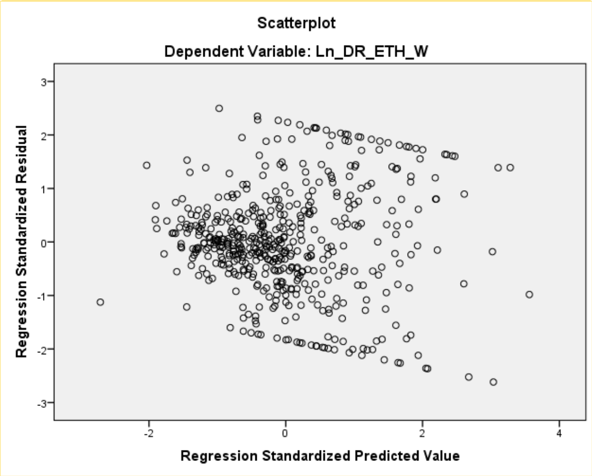
Ripple



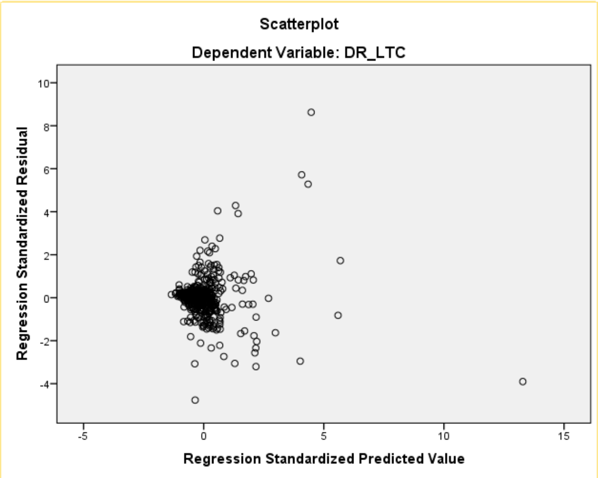


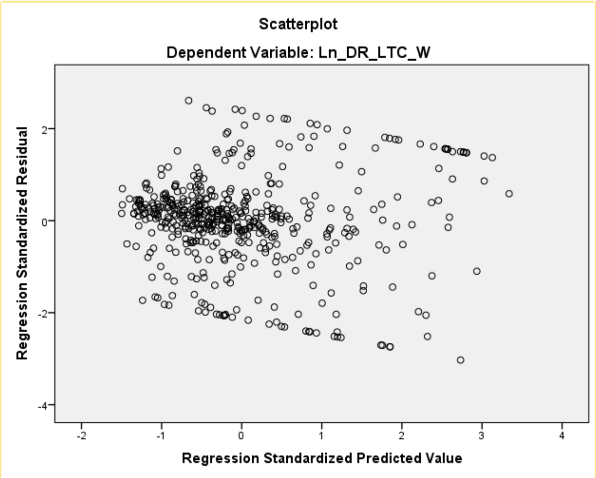
Ethereum



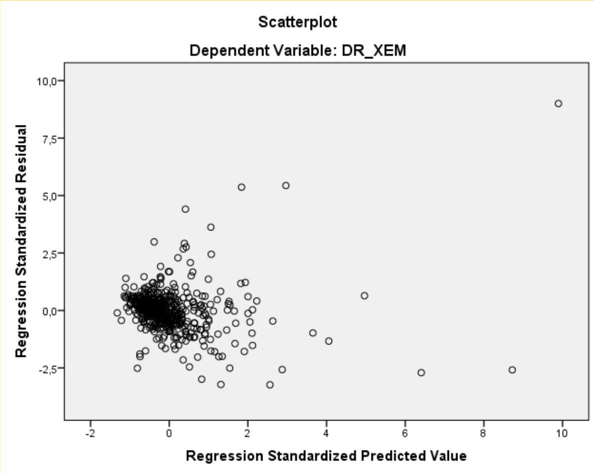


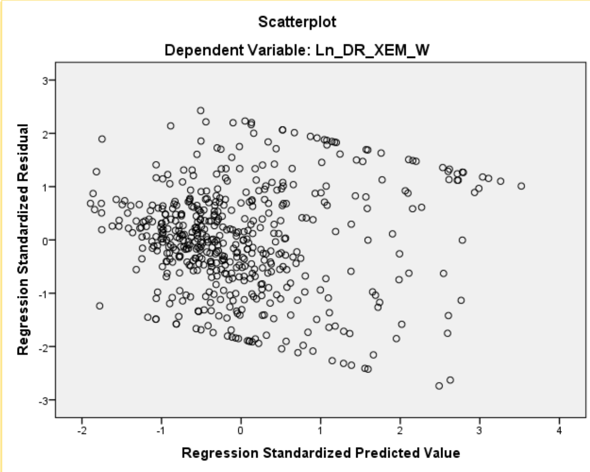
Litecoin



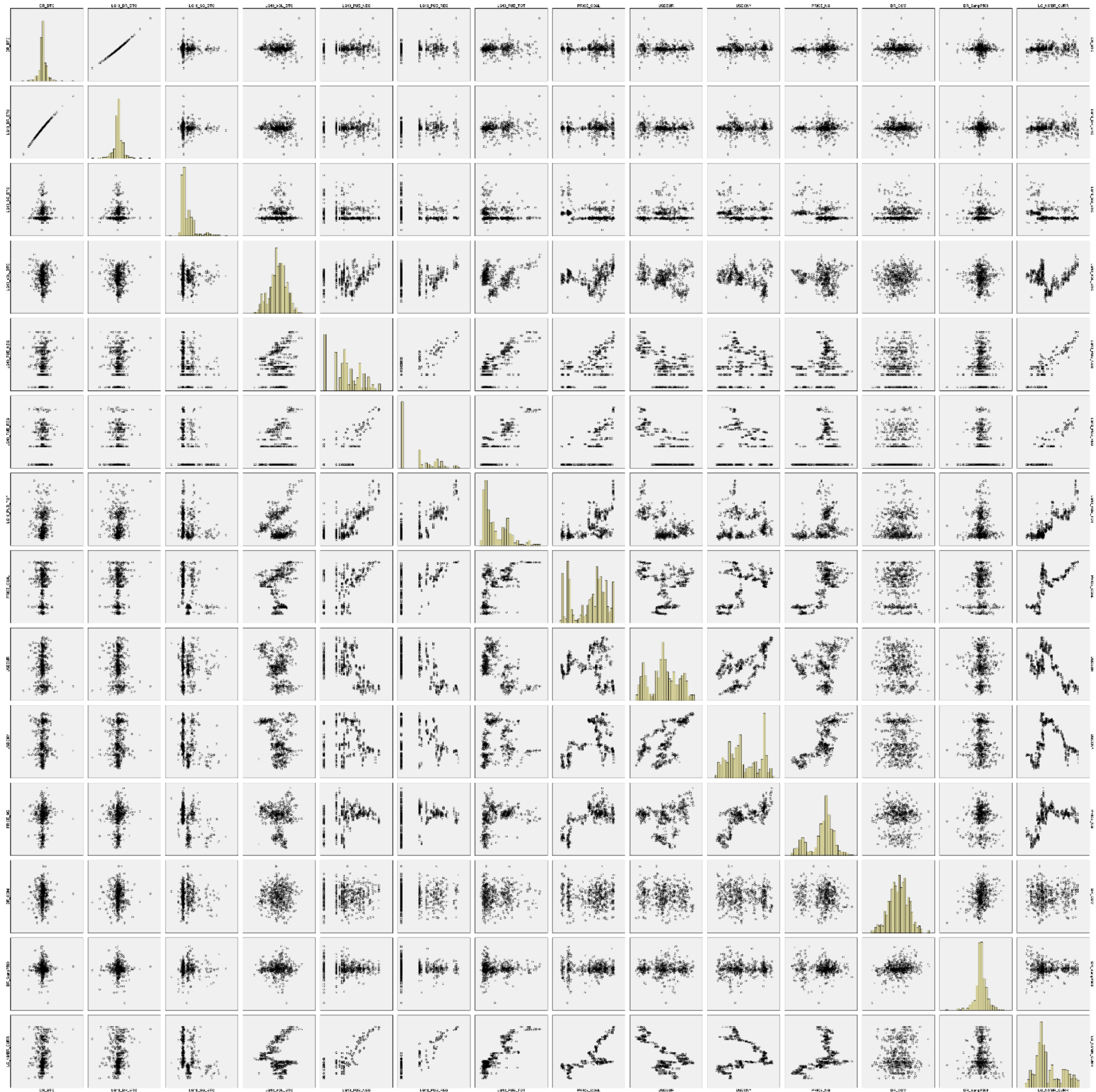


XEM

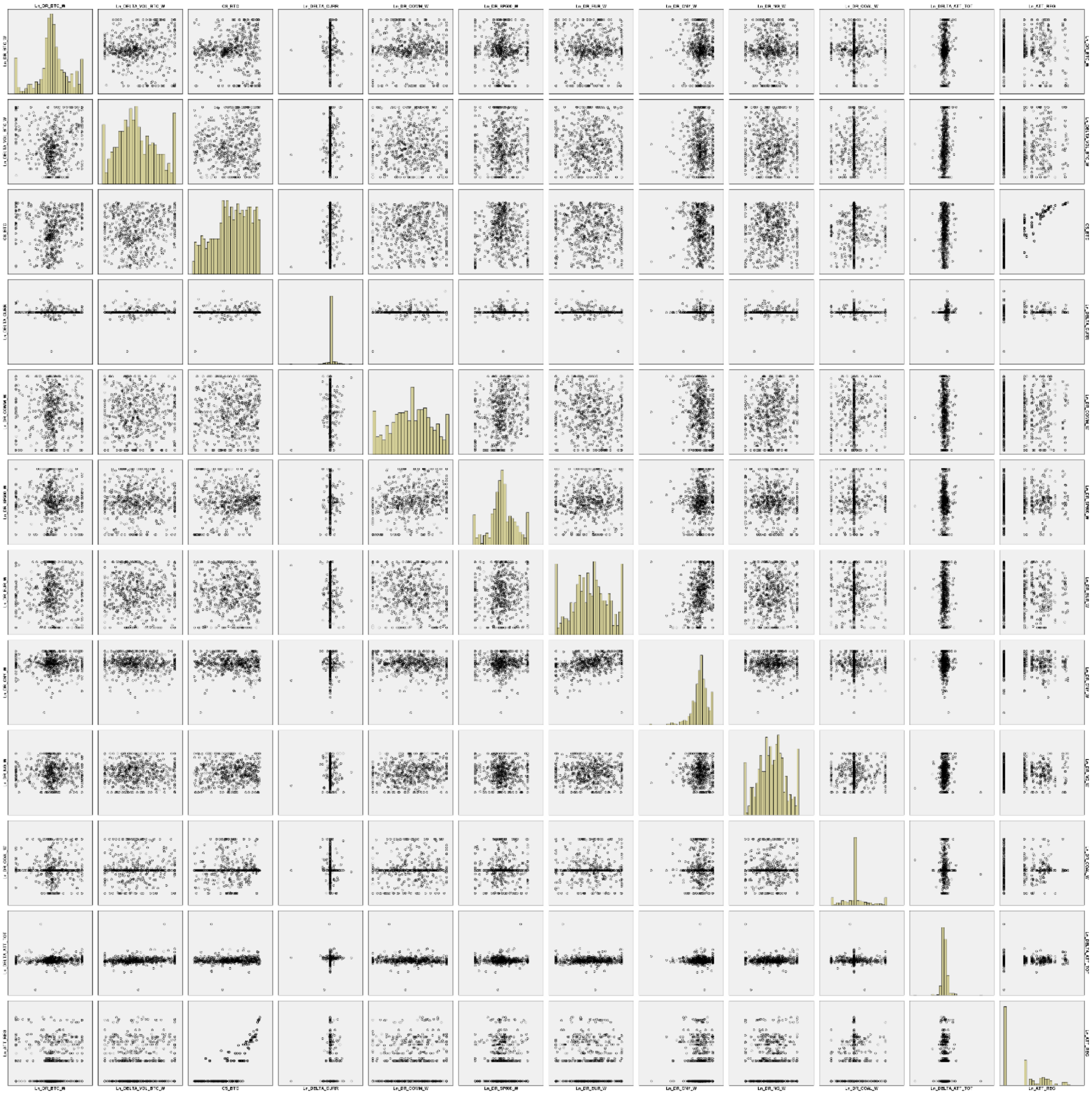

Scatterplot
Dependent Variable: DR_XEM
Regression Standardized Residual
Regression Standardized Predicted Value
10,0
7,5
5,0
2,5
0,0
-2,5
-2
0
2
4
6
8
10


Scatterplot
Dependent Variable: Ln_DR_XEM_W
Regression Standardized Residual
Regression Standardized Predicted Value
3
2
1
0
-1
-2
-3
-2
-1
0
1
2
3
4

Linearity of the phenomenon measured



Scatter matrix Bitcoin variables before data transformation and corrective measures residuals.



Scatter matrix Bitcoin variables after data transformation and corrective measures residuals

9.6 RAW DATA REGRESSION ANALYSES

9.6.1 Bitcoin

Model 1 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,119[a]	.014	.006	.021257195327328	.014	1.843	2	256	.160	1.918

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.030	.066		-.447	.655	-.160	.101		
	PRICE_NG_W	.005	.003	.107	1.485	.139	-.002	.011	.738	1.355
	EUR_W	.022	.078	.021	.285	.776	-.131	.175	.738	1.355

a. Dependent Variable: Ln_DR_BTC_W

Model 2 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,213[a]	.045	.015	.021126569592873	.045	1.488	8	251	.162	1.990

a. Predictors: (Constant), CNY_W, DR_SP500_W, Ln_ATT_TOT, ATTENTION_REG, DR_COMM_W, ATTENTION_NEG, SG_BTC, CURR

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.145	.096		-1.504	.134	-.334	.045		
	CURR	4.042E-05	.000	.102	1.212	.226	.000	.000	.537	1.864
	DR_COMM_W	.344	.258	.087	1.330	.185	-.165	.853	.891	1.123
	DR_SP500_W	-.260	.236	-.071	-1.101	.272	-.725	.205	.913	1.096
	SG_BTC	3.022	7.417	.028	.407	.684	-11.585	17.629	.818	1.223
	ATTENTION_NEG	.000	.000	.074	1.128	.260	.000	.001	.884	1.131
	ATTENTION_REG	.000	.001	.026	.395	.693	-.001	.001	.912	1.096
	Ln_ATT_TOT	.006	.006	.069	1.062	.289	-.005	.018	.912	1.096
	CNY_W	.009	.014	.055	.650	.516	-.018	.037	.534	1.871

a. Dependent Variable: Ln_DR_BTC_W

Model 3 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,161[a]	.026	.014	.021131318912131	.026	2.263	3	256	.082	1.941

a. Predictors: (Constant), CNY_W, DELTA_VOL_BTC_W, SG_BTC

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.160	.073		-2.199	.029	-.303	-.017		
	SG_BTC	1.783	7.138	.016	.250	.803	-12.273	15.840	.884	1.132
	DELTA_VOL_BTC_W	.005	.004	.077	1.252	.212	-.003	.012	.999	1.001
	CNY_W	.024	.011	.147	2.241	.026	.003	.046	.884	1.131

a. Dependent Variable: Ln_DR_BTC_W

Model 4 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,229[a]	.053	.014	.021173064070096	.053	1.375	10	248	.192	2.009

a. Predictors: (Constant), EUR_W, DELTA_VOL_BTC_W, DR_SP500_W, Ln_ATT_TOT, ATTENTION_REG, ATTENTION_NEG, SG_BTC, DR_COMM_W, CURR, PRICE_NG_W

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.174	.099		-1.764	.079	-.368	.020		
	CURR	7.444E-05	.000	.188	1.657	.099	.000	.000	.298	3.359
	DR_COMM_W	.339	.259	.086	1.308	.192	-.171	.849	.889	1.125
	DR_SP500_W	-.250	.236	-.068	-1.058	.291	-.716	.216	.913	1.095
	SG_BTC	2.412	7.454	.022	.324	.747	-12.269	17.093	.813	1.229
	ATTENTION_NEG	.000	.000	.071	1.089	.277	.000	.001	.895	1.117
	ATTENTION_REG	.000	.001	.020	.307	.759	-.001	.001	.910	1.099
	Ln_ATT_TOT	.006	.006	.062	.964	.336	-.006	.018	.910	1.099
	PRICE_NG_W	-.003	.006	-.077	-.613	.540	-.014	.008	.240	4.167
	DELTA_VOL_BTC_W	.004	.004	.067	1.083	.280	-.003	.012	.987	1.013
	EUR_W	.093	.089	.086	1.037	.301	-.083	.269	.554	1.806

a. Dependent Variable: Ln_DR_BTC_W

Model 1 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,073[a]	.005	-.002	.037487979771145	.005	.693	2	256	.501	1.823

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.018	.055		.331	.741	-.091	.127		
	PRICE_NG_W	.015	.015	.071	1.020	.309	-.014	.044	.808	1.237
	EUR_W	-.064	.065	-.068	-.975	.331	-.192	.065	.808	1.237

a. Dependent Variable: Ln_DR_BTC_W

Model 2 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,080[a]	.006	-.009	.037540989644872	.006	.415	4	255	.798	1.822

a. Predictors: (Constant), SG_BTC, CURR, DR_SP500_W, DR_COMM_W

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.002	.011		-.163	.870	-.024	.020		
	CURR	5.206E-06	.000	.030	.470	.639	.000	.000	.987	1.013
	DR_COMM_W	-.265	.468	-.036	-.566	.572	-1.186	.656	.963	1.039
	DR_SP500_W	.166	.615	.017	.271	.787	-1.045	1.378	.975	1.026
	SG_BTC	24.158	23.459	.064	1.030	.304	-22.040	70.355	.995	1.005

a. Dependent Variable: Ln_DR_BTC_W

Model 3 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,085[a]	.007	-.004	.037453834232106	.007	.619	3	256	.604	1.798

a. Predictors: (Constant), EUR_W, SG_BTC, DELTA_VOL_BTC_W

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.033	.052		.630	.529	-.070	.135		
	SG_BTC	26.906	23.527	.072	1.144	.254	-19.426	73.238	.985	1.015
	DELTA_VOL_BTC_W	-.003	.005	-.037	-.591	.555	-.013	.007	.982	1.018
	EUR_W	-.033	.058	-.036	-.572	.568	-.149	.082	.997	1.003

a. Dependent Variable: Ln_DR_BTC_W

Model 4 – 2017

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.004	6	.001	.480	,823[b]
	Residual	.358	252	.001		
	Total	.362	258			

a. Dependent Variable: Ln_DR_BTC_W

b. Predictors: (Constant), DELTA_VOL_BTC_W, DR_COMM_W, PRICE_NG_W, SG_BTC, DR_SP500_W, CURR

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.049	.053		-.934	.351	-.154	.055		
	PRICE_NG_W	.014	.015	.067	.929	.354	-.016	.044	.752	1.329
	CURR	1.083E-05	.000	.061	.845	.399	.000	.000	.746	1.341
	DR_COMM_W	-.280	.470	-.038	-.595	.552	-1.205	.646	.961	1.040
	DR_SP500_W	.199	.618	.020	.322	.748	-1.018	1.416	.973	1.028
	SG_BTC	25.177	23.736	.067	1.061	.290	-21.570	71.924	.980	1.020
	DELTA_VOL_BTC_W	-.003	.005	-.032	-.510	.610	-.013	.008	.973	1.028

a. Dependent Variable: Ln_DR_BTC_W

Model 1 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,088[a]	.008	.004	.030614224996461	.008	1.962	2	508	.142	1.811

a. Predictors: (Constant), CNY_W, PRICE_COAL_W

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	-.057	.070		-.812	.417	-.195	.081		
	PRICE_COAL_W	.000	.000	.065	1.290	.198	.000	.001	.768	1.302
	CNY_W	.008	.011	.035	.696	.486	-.014	.029	.768	1.302

a. Dependent Variable: Ln_DR_BTC_W

Model 2 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,118[a]	.014	.004	.030403460041252	.014	1.447	5	514	.206	1.842

a. Predictors: (Constant), CNY_W, DR_SP500_W, CURR, DR_COMM_W, SG_BTC

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	-.131	.068		-1.919	.056	-.266	.003		
	CURR	1.279E-05	.000	.096	2.100	.036	.000	.000	.918	1.090
	DR_COMM_W	.013	.264	.002	.048	.961	-.505	.531	.936	1.069
	DR_SP500_W	-.098	.279	-.016	-.353	.724	-.646	.449	.945	1.058
	SG_BTC	7.826	9.015	.042	.868	.386	-9.884	25.536	.838	1.193
	CNY_W	.019	.010	.086	1.859	.064	-.001	.038	.894	1.119

a. Dependent Variable: Ln_DR_BTC_W

Model 3 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,072[a]	.005	-.001	.030476976039065	.005	.908	3	516	.437	1.830

a. Predictors: (Constant), CNY_W, DELTA_VOL_BTC_W, SG_BTC

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.104	.067		-1.541	.124	-.236	.029		
	DELTA_VOL_BTC_W	.000	.003	.006	.146	.884	-.006	.007	.994	1.006
	SG_BTC	2.371	8.669	.013	.273	.785	-14.660	19.401	.911	1.098
	CNY_W	.016	.010	.074	1.615	.107	-.003	.036	.907	1.103

a. Dependent Variable: Ln_DR_BTC_W

Model 4 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,120[a]	.014	.001	.030515645770093	.014	1.056	7	510	.391	1.844

a. Predictors: (Constant), CNY_W, DR_SP500_W, CURR, DELTA_VOL_BTC_W, DR_COMM_W, SG_BTC, PRICE_NG_W

b. Dependent Variable: Ln_DR_BTC_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.094	.107		-.879	.380	-.305	.117		
	PRICE_NG_W	.003	.006	.041	.460	.646	-.009	.015	.244	4.102
	CURR	1.062E-05	.000	.080	1.357	.176	.000	.000	.560	1.784
	DR_COMM_W	.015	.265	.003	.055	.956	-.506	.535	.936	1.069
	DR_SP500_W	-.095	.280	-.015	-.338	.735	-.644	.455	.944	1.059
	SG_BTC	8.494	9.167	.045	.927	.355	-9.517	26.504	.817	1.224
	DELTA_VOL_BTC_W	-7.077E-05	.003	-.001	-.021	.983	-.007	.006	.980	1.020
	CNY_W	.012	.018	.056	.690	.490	-.022	.047	.295	3.392

a. Dependent Variable: Ln_DR_BTC_W

9.6.2 Ripple

Model 1 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,059[a]	.004	-.004	.030860383276695	.004	.454	2	256	.636	1.812

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.074	.096		.773	.441	-.115	.264		
	PRICE_NG_W	.004	.005	.061	.841	.401	-.005	.013	.738	1.355
	EUR_W	-.092	.113	-.059	-.815	.416	-.314	.130	.738	1.355

a. Dependent Variable: Ln_DR_XRP_W

Model 2 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,215[a]	.046	.016	.030492515127173	.046	1.523	8	251	.150	1.852

a. Predictors: (Constant), CNY_W, DR_SP500_W, SG_XRP, Ln_ATT_TOT, ATTENTION_REG, DR_COMM_W, ATTENTION_NEG, CURR
b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.222	.138		1.608	.109	-.050	.494		
	CURR	4.589E-05	.000	.080	.972	.332	.000	.000	.557	1.795
	DR_COMM_W	-.094	.373	-.017	-.253	.801	-.830	.641	.889	1.125
	DR_SP500_W	.577	.341	.109	1.691	.092	-.095	1.249	.909	1.100
	SG_XRP	1.201	1.118	.067	1.074	.284	-1.001	3.403	.984	1.016
	ATTENTION_NEG	-.001	.001	-.100	-1.528	.128	-.002	.000	.882	1.134
	ATTENTION_REG	-.001	.001	-.060	-.932	.352	-.002	.001	.912	1.096
	Ln_ATT_TOT	-.019	.009	-.140	-2.211	.028	-.036	-.002	.942	1.062
	CNY_W	-.010	.020	-.040	-.485	.628	-.049	.030	.546	1.830

a. Dependent Variable: Ln_DR_XRP_W

Model 3 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,237[a]	.056	.045	.030037384137277	.056	5.073	3	256	.002	1.831

a. Predictors: (Constant), CNY_W, DELTA_VOL_XRP_W, SG_XRP

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.070	.096		.722	.471	-.120	.259		
	SG_XRP	.799	1.096	.044	.730	.466	-1.358	2.957	.994	1.006
	DELTA_VOL_XRP_W	.011	.003	.225	3.695	.000	.005	.017	.994	1.006
	CNY_W	-.011	.015	-.045	-.735	.463	-.039	.018	1.000	1.000

a. Dependent Variable: Ln_DR_XRP_W

Model 4 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,318[a]	.101	.065	.029781082095619	.101	2.787	10	248	.003	1.877

a. Predictors: (Constant), EUR_W, DELTA_VOL_XRP_W, Ln_ATT_TOT, DR_SP500_W, SG_XRP, ATTENTION_REG, ATTENTION_NEG, DR_COMM_W, CURR, PRICE_NG_W

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.301	.139		2.167	.031	.027	.574		
	CURR	-4.194E-05	.000	-.073	-.669	.504	.000	.000	.302	3.306
	DR_COMM_W	-.070	.365	-.012	-.193	.847	-.789	.648	.887	1.127
	DR_SP500_W	.478	.334	.091	1.431	.154	-.180	1.136	.905	1.105
	SG_XRP	.958	1.096	.053	.874	.383	-1.201	3.117	.977	1.024
	ATTENTION_NEG	-.001	.001	-.089	-1.392	.165	-.002	.000	.890	1.124
	ATTENTION_REG	-.001	.001	-.077	-1.217	.225	-.002	.001	.909	1.101
	Ln_ATT_TOT	-.019	.008	-.137	-2.201	.029	-.035	-.002	.942	1.062
	PRICE_NG_W	.012	.008	.184	1.509	.132	-.004	.027	.243	4.118
	DELTA_VOL_XRP_W	.011	.003	.220	3.616	.000	.005	.016	.980	1.020
	EUR_W	-.142	.126	-.092	-1.129	.260	-.391	.106	.551	1.816

a. Dependent Variable: Ln_DR_XRP_W

Model 1 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,027[a]	.001	-.007	.059808870055914	.001	.092	2	256	.912	1.807

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.002	.088		.028	.977	-.171	.176		
	PRICE_NG_W	.010	.023	.030	.429	.669	-.036	.056	.808	1.237
	EUR_W	-.021	.104	-.014	-.199	.842	-.226	.184	.808	1.237

a. Dependent Variable: Ln_DR_XRP_W

Model 2 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,147[a]	.022	.006	.059319375662046	.022	1.404	4	255	.233	1.853

a. Predictors: (Constant), SG_XRP, DR_SP500_W, ATTENTION_NEG, DR_COMM_W

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.006	.005		1.062	.289	-.005	.016		
	ATTENTION_NEG	.000	.000	.129	2.063	.040	.000	.001	.983	1.017
	DR_COMM_W	.483	.737	.041	.655	.513	-.969	1.934	.968	1.033
	DR_SP500_W	.083	.971	.005	.086	.932	-1.829	1.995	.977	1.023
	SG_XRP	2.145	2.245	.059	.955	.340	-2.277	6.566	.992	1.008

a. Dependent Variable: Ln_DR_XRP_W

Model 3 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,472[a]	.222	.213	.052775384287387	.222	24.418	3	256	.000	1.923

a. Predictors: (Constant), EUR_W, DELTA_VOL_XRP_W, SG_XRP

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.027	.074		.366	.715	-.118	.172		
	SG_XRP	.506	2.011	.014	.251	.802	-3.455	4.466	.979	1.022
	DELTA_VOL_XRP_W	.035	.004	.471	8.515	.000	.027	.043	.994	1.006
	EUR_W	-.028	.083	-.018	-.332	.740	-.191	.136	.983	1.017

a. Dependent Variable: Ln_DR_XRP_W

Model 4 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,493[a]	.243	.225	.052475031042725	.243	13.466	6	252	.000	1.969

a. Predictors: (Constant), DELTA_VOL_XRP_W, DR_COMM_W, PRICE_NG_W, SG_XRP, DR_SP500_W, ATTENTION_NEG

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.120	.066		-1.836	.067	-.249	.009		
	PRICE_NG_W	.038	.021	.113	1.798	.073	-.004	.079	.764	1.308
	ATTENTION_NEG	.000	.000	.146	2.317	.021	.000	.001	.756	1.322
	DR_COMM_W	.493	.652	.042	.755	.451	-.792	1.777	.967	1.034
	DR_SP500_W	-.432	.861	-.028	-.501	.616	-2.128	1.264	.972	1.029
	SG_XRP	.546	1.997	.015	.273	.785	-3.388	4.479	.981	1.019
	DELTA_VOL_XRP_W	.034	.004	.465	8.417	.000	.026	.042	.983	1.018

a. Dependent Variable: Ln_DR_XRP_W

Model 1 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,074[a]	.006	.002	.048040302101270	.006	1.414	2	508	.244	1.805

a. Predictors: (Constant), CNY_W, PRICE_COAL_W

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.042	.110		-.380	.704	-.258	.175		
	PRICE_COAL_W	.000	.000	.066	1.313	.190	.000	.001	.768	1.302
	CNY_W	.005	.017	.015	.288	.773	-.029	.039	.768	1.302

a. Dependent Variable: Ln_DR_XRP_W

Model 2 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,192[a]	.037	.027	.047089273132742	.037	3.932	5	514	.002	1.841

a. Predictors: (Constant), CNY_W, DR_SP500_W, SG_XRP, ATTENTION_NEG, DR_COMM_W

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.158	.100		-1.573	.116	-.355	.039		
	ATTENTION_NEG	.000	.000	.173	3.924	.000	.000	.001	.965	1.036
	DR_COMM_W	.308	.408	.034	.756	.450	-.493	1.110	.938	1.066
	DR_SP500_W	.379	.431	.039	.879	.380	-.468	1.227	.944	1.059
	SG_XRP	1.569	1.236	.055	1.269	.205	-.860	3.998	.994	1.006
	CNY_W	.024	.015	.070	1.591	.112	-.006	.053	.965	1.037

a. Dependent Variable: Ln_DR_XRP_W

Model 3 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,401[a]	.161	.156	.043873397081430	.161	32.920	3	516	.000	1.878

a. Predictors: (Constant), CNY_W, DELTA_VOL_XRP_W, SG_XRP

b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	-.065	.092		-.704	.482	-.245	.116		
	DELTA_VOL_XRP_W	.026	.003	.397	9.825	.000	.021	.031	.994	1.006
	SG_XRP	.454	1.152	.016	.394	.694	-1.810	2.717	.993	1.007
	CNY_W	.010	.014	.029	.709	.479	-.017	.037	.997	1.003

a. Dependent Variable: Ln_DR_XRP_W

Model 4 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,436[a]	.190	.178	.043580125818461	.190	16.820	7	503	.000	1.944

a. Predictors: (Constant), CNY_W, DR_SP500_W, SG_XRP, DELTA_VOL_XRP_W, ATTENTION_NEG, DR_COMM_W, PRICE_COAL_W
b. Dependent Variable: Ln_DR_XRP_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	-.312	.121		-2.571	.010	-.550	-.074		
	PRICE_COAL_W	-.001	.000	-.154	-2.265	.024	-.001	.000	.349	2.865
	ATTENTION_NEG	.001	.000	.238	3.922	.000	.000	.001	.439	2.279
	DR_COMM_W	.293	.379	.032	.773	.440	-.451	1.036	.937	1.068
	DR_SP500_W	.103	.401	.011	.256	.798	-.685	.890	.939	1.065
	SG_XRP	.589	1.149	.021	.513	.608	-1.668	2.846	.986	1.014
	DELTA_VOL_XRP_W	.025	.003	.382	9.426	.000	.020	.030	.979	1.021
	CNY_W	.051	.020	.150	2.610	.009	.013	.090	.489	2.046

a. Dependent Variable: Ln_DR_XRP_W

9.6.3 Ethereum

Model 1 – 2016

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,117[a]	.014	.006	.056829773030376	.014	1.788	2	256	.169	2.040

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.126	.178		-.710	.478	-.476	.224		
	PRICE_NG_W	-.016	.009	-.137	-1.891	.060	-.033	.001	.738	1.355
	EUR_W	.195	.208	.068	.936	.350	-.215	.604	.738	1.355

a. Dependent Variable: Ln_DR_ETH_W

Model 2 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,271[a]	.073	.044	.055723198715791	.073	2.487	8	251	.013	2.092

a. Predictors: (Constant), CNY_W, DR_SP500_W, SG_ETH, Ln_ATT_TOT, ATTENTION_REG, ATTENTION_NEG, DR_COMM_W, CURR

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.336	.252		-1.331	.184	-.833	.161		
	CURR	.000	.000	-.166	-2.047	.042	.000	.000	.558	1.791
	DR_COMM_W	-.689	.684	-.065	-1.007	.315	-2.036	.658	.884	1.131
	DR_SP500_W	-.318	.623	-.033	-.511	.610	-1.544	.908	.912	1.096
	SG_ETH	-11.245	9.294	-.074	-1.210	.227	-29.550	7.060	.981	1.020
	ATTENTION_NEG	-.002	.001	-.100	-1.551	.122	-.004	.000	.886	1.129
	ATTENTION_REG	-.001	.001	-.054	-.850	.396	-.004	.002	.913	1.095
	Ln_ATT_TOT	.035	.016	.138	2.201	.029	.004	.066	.938	1.066
	CNY_W	.020	.036	.045	.546	.586	-.052	.092	.545	1.833

a. Dependent Variable: Ln_DR_ETH_W

Model 3 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,150[a]	.022	.011	.056676869315061	.022	1.953	3	256	.122	2.065

a. Predictors: (Constant), CNY_W, SG_ETH, DELTA_VOL_ETH_W

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.296	.183		1.615	.107	-.065	.656		
	SG_ETH	-13.051	9.375	-.086	-1.392	.165	-31.513	5.412	.997	1.003
	DELTA_VOL_ETH_W	.007	.005	.092	1.480	.140	-.002	.017	.992	1.008
	CNY_W	-.042	.028	-.096	-1.543	.124	-.097	.012	.990	1.010

a. Dependent Variable: Ln_DR_ETH_W

Model 4 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,278[a]	.077	.040	.055843568201397	.077	2.083	10	248	.026	2.147

a. Predictors: (Constant), EUR_W, DR_SP500_W, Ln_ATT_TOT, SG_ETH, ATTENTION_REG, DELTA_VOL_ETH_W, ATTENTION_NEG, DR_COMM_W, CURR, PRICE_NG_W

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.196	.261		-.752	.453	-.710	.318		
	CURR	.000	.000	-.168	-1.506	.133	.000	.000	.301	3.326
	DR_COMM_W	-.666	.686	-.063	-.971	.333	-2.018	.686	.882	1.134
	DR_SP500_W	-.344	.624	-.035	-.550	.582	-1.573	.886	.911	1.098
	SG_ETH	-11.681	9.336	-.077	-1.251	.212	-30.070	6.707	.976	1.024
	ATTENTION_NEG	-.002	.001	-.100	-1.553	.122	-.004	.000	.895	1.118
	ATTENTION_REG	-.001	.001	-.049	-.769	.442	-.004	.002	.913	1.095
	Ln_ATT_TOT	.032	.016	.128	2.021	.044	.001	.064	.924	1.082
	PRICE_NG_W	.004	.015	.036	.289	.773	-.025	.033	.242	4.127
	DELTA_VOL_ETH_W	.005	.005	.064	1.037	.301	-.005	.015	.966	1.035
	EUR_W	.005	.236	.002	.020	.984	-.461	.470	.551	1.816

a. Dependent Variable: Ln_DR_ETH_W

Model 1 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,059[a]	.003	-.004	.058363557312572	.003	.448	2	256	.639	1.749

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.059	.086		-.689	.492	-.229	.110		
	PRICE_NG_W	-.002	.023	-.007	-.103	.918	-.047	.043	.808	1.237
	EUR_W	.090	.102	.062	.891	.374	-.109	.290	.808	1.237

a. Dependent Variable: Ln_DR_ETH_W

Model 2 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,100[a]	.010	-.006	.058400837019131	.010	.644	4	255	.631	1.760

a. Predictors: (Constant), SG_ETH, DR_SP500_W, DR_COMM_W, ATTENTION_REG

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.013	.008		1.686	.093	-.002	.028		
	ATTENTION_REG	-3.205E-05	.000	-.016	-.243	.808	.000	.000	.943	1.060
	DR_COMM_W	1.002	.726	.087	1.380	.169	-.428	2.432	.968	1.034
	DR_SP500_W	.563	.957	.037	.588	.557	-1.321	2.447	.975	1.025
	SG_ETH	1.508	14.056	.007	.107	.915	-26.172	29.189	.941	1.062

a. Dependent Variable: Ln_DR_ETH_W

Model 3 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,326[a]	.106	.096	.055379471060580	.106	10.150	3	256	.000	1.891

a. Predictors: (Constant), EUR_W, DELTA_VOL_ETH_W, SG_ETH

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.046	.080		-.578	.564	-.203	.111		
	SG_ETH	-13.174	13.857	-.060	-.951	.343	-40.462	14.114	.871	1.148
	DELTA_VOL_ETH_W	.029	.005	.325	5.440	.000	.019	.040	.975	1.025
	EUR_W	.066	.092	.045	.721	.472	-.115	.247	.885	1.130

a. Dependent Variable: Ln_DR_ETH_W

Model 4 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,337[a]	.114	.092	.055480126701460	.114	5.382	6	252	.000	1.899

a. Predictors: (Constant), DELTA_VOL_ETH_W, DR_SP500_W, ATTENTION_REG, DR_COMM_W, SG_ETH, PRICE_NG_W

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.003	.069		-.042	.967	-.138	.133		
	PRICE_NG_W	.005	.022	.014	.213	.832	-.039	.049	.766	1.306
	ATTENTION_REG	-3.009E-05	.000	-.015	-.213	.831	.000	.000	.743	1.346
	DR_COMM_W	1.044	.690	.091	1.513	.132	-.315	2.402	.967	1.034
	DR_SP500_W	.538	.909	.036	.592	.555	-1.253	2.329	.975	1.026
	SG_ETH	-9.818	13.532	-.045	-.726	.469	-36.469	16.832	.916	1.091
	DELTA_VOL_ETH_W	.029	.005	.325	5.419	.000	.019	.040	.977	1.024

a. Dependent Variable: Ln_DR_ETH_W

Model 1 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,050[a]	.002	-.001	.057765674721170	.002	.634	2	508	.531	1.903

a. Predictors: (Constant), CNY_W, PRICE_COAL_W

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.069	.132		-.523	.601	-.330	.191		
	PRICE_COAL_W	.000	.000	-.056	-1.110	.267	-.001	.000	.768	1.302
	CNY_W	.014	.021	.035	.699	.485	-.026	.055	.768	1.302

a. Dependent Variable: Ln_DR_ETH_W

Model 2 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,055[a]	.003	-.007	.057814439304157	.003	.311	5	514	.907	1.871

a. Predictors: (Constant), CNY_W, SG_ETH, DR_SP500_W, DR_COMM_W, ATTENTION_REG

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.023	.124		-.188	.851	-.267	.220		
	ATTENTION_REG	3.377E-06	.000	.001	.029	.977	.000	.000	.910	1.098
	DR_COMM_W	.048	.501	.004	.097	.923	-.936	1.032	.938	1.066
	DR_SP500_W	-.077	.530	-.007	-.146	.884	-1.119	.964	.944	1.060
	SG_ETH	-9.017	7.801	-.052	-1.156	.248	-24.343	6.309	.946	1.057
	CNY_W	.006	.018	.014	.312	.756	-.030	.042	.956	1.046

a. Dependent Variable: Ln_DR_ETH_W

Model 3 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,205[a]	.042	.036	.056562327627991	.042	7.544	3	516	.000	1.946

a. Predictors: (Constant), CNY_W, SG_ETH, DELTA_VOL_ETH_W

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.013	.118		.113	.910	-.219	.246		
	DELTA_VOL_ETH_W	.017	.004	.199	4.587	.000	.009	.024	.990	1.010
	SG_ETH	-11.508	7.442	-.067	-1.546	.123	-26.129	3.112	.995	1.005
	CNY_W	.000	.018	.000	-.006	.995	-.035	.035	.995	1.005

a. Dependent Variable: Ln_DR_ETH_W

Model 4 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,225[a]	.050	.037	.056639412290504	.050	3.818	7	503	.000	1.996

a. Predictors: (Constant), CNY_W, SG_ETH, DR_SP500_W, DELTA_VOL_ETH_W, DR_COMM_W, ATTENTION_REG, PRICE_COAL_W

b. Dependent Variable: Ln_DR_ETH_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.171	.159		-1.074	.284	-.483	.142		
	PRICE_COAL_W	-.001	.000	-.146	-1.993	.047	-.002	.000	.351	2.849
	ATTENTION_REG	.000	.000	.092	1.413	.158	.000	.001	.443	2.256
	DR_COMM_W	.135	.492	.012	.274	.784	-.832	1.102	.936	1.069
	DR_SP500_W	-.135	.520	-.012	-.259	.796	-1.156	.887	.942	1.061
	SG_ETH	-15.160	7.787	-.088	-1.947	.052	-30.459	.139	.931	1.074
	DELTA_VOL_ETH_W	.016	.004	.194	4.424	.000	.009	.023	.984	1.016
	CNY_W	.034	.026	.082	1.309	.191	-.017	.084	.479	2.089

a. Dependent Variable: Ln_DR_ETH_W

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Model 1 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,012[a]	.000	-.008	.026107059860920	.000	.018	2	256	.982	2.059

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.009	.082		.110	.913	-.152	.170		
	PRICE_NG_W	.001	.004	.014	.189	.850	-.007	.008	.738	1.355
	EUR_W	-.011	.095	-.009	-.118	.906	-.199	.177	.738	1.355

a. Dependent Variable: Ln_DR_LTC_W

Model 2 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,149[a]	.022	-.009	.026074815117158	.022	.710	8	251	.682	2.092

a. Predictors: (Constant), CNY_W, DR_SP500_W, SG_LTC, Ln_ATT_TOT, ATTENTION_REG, ATTENTION_NEG, DR_COMM_W, CURR

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.003	.118		.028	.978	-.229	.236		
	CURR	3.768E-05	.000	.078	.935	.351	.000	.000	.559	1.789
	DR_COMM_W	.452	.319	.094	1.416	.158	-.176	1.080	.889	1.124
	DR_SP500_W	-.344	.291	-.077	-1.183	.238	-.918	.229	.913	1.096
	SG_LTC	-3.162	6.306	-.031	-.501	.617	-15.582	9.258	.990	1.010
	ATTENTION_NEG	.001	.001	.072	1.088	.277	.000	.002	.886	1.129
	ATTENTION_REG	6.152E-05	.001	.006	.092	.927	-.001	.001	.914	1.094
	Ln_ATT_TOT	.006	.007	.051	.790	.430	-.009	.020	.935	1.069
	CNY_W	-.012	.017	-.060	-.709	.479	-.046	.021	.549	1.822

a. Dependent Variable: Ln_DR_LTC_W

Model 3 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,075[a]	.006	-.006	.026036942232998	.006	.476	3	256	.699	2.049

a. Predictors: (Constant), CNY_W, DELTA_VOL_LTC_W, SG_LTC

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.015	.084		-.178	.859	-.180	.150		
	SG_LTC	-1.634	6.363	-.016	-.257	.797	-14.164	10.896	.970	1.031
	DELTA_VOL_LTC_W	.004	.004	.069	1.088	.278	-.003	.011	.970	1.031
	CNY_W	.002	.013	.012	.191	.848	-.022	.027	.999	1.001

a. Dependent Variable: Ln_DR_LTC_W

Model 4 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,170[a]	.029	-.010	.026142058292702	.029	.735	10	248	.691	2.095

a. Predictors: (Constant), EUR_W, DR_SP500_W, SG_LTC, ATTENTION_REG, Ln_ATT_TOT, DELTA_VOL_LTC_W, ATTENTION_NEG, DR_COMM_W, CURR, PRICE_NG_W

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.122	.122		-1.002	.317	-.362	.118		
	CURR	6.929E-05	.000	.143	1.257	.210	.000	.000	.301	3.319
	DR_COMM_W	.433	.321	.090	1.351	.178	-.199	1.065	.885	1.130
	DR_SP500_W	-.324	.293	-.073	-1.106	.270	-.901	.253	.906	1.104
	SG_LTC	-1.898	6.428	-.019	-.295	.768	-14.559	10.763	.959	1.043
	ATTENTION_NEG	.000	.001	.060	.913	.362	-.001	.001	.895	1.117
	ATTENTION_REG	2.887E-05	.001	.003	.043	.966	-.001	.001	.915	1.092
	Ln_ATT_TOT	.005	.007	.046	.717	.474	-.009	.020	.935	1.069
	PRICE_NG_W	-.007	.007	-.134	-1.054	.293	-.021	.006	.243	4.121
	DELTA_VOL_LTC_W	.004	.004	.067	1.047	.296	-.003	.011	.955	1.047
	EUR_W	.055	.110	.042	.496	.620	-.163	.272	.554	1.806

a. Dependent Variable: Ln_DR_LTC_W

Model 1 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,039[a]	.002	-.006	.052919511805478	.002	.195	2	256	.823	1.924

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.054	.078		.695	.488	-.100	.208		
	PRICE_NG_W	-.004	.021	-.012	-.176	.861	-.044	.037	.808	1.237
	EUR_W	-.043	.092	-.032	-.462	.644	-.224	.139	.808	1.237

a. Dependent Variable: Ln_DR_LTC_W

Model 2 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,109[a]	.012	-.004	.052770258352448	.012	.770	4	255	.546	1.939

a. Predictors: (Constant), SG_LTC, Ln_ATT_TOT, DR_SP500_W, DR_COMM_W

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.030	.049		-.603	.547	-.127	.068		
	Ln_ATT_TOT	.003	.005	.038	.610	.543	-.006	.012	.994	1.006
	DR_COMM_W	.072	.655	.007	.110	.912	-1.217	1.362	.971	1.030
	DR_SP500_W	1.112	.865	.081	1.285	.200	-.592	2.816	.973	1.027
	SG_LTC	11.882	13.372	.055	.889	.375	-14.452	38.215	.994	1.006

a. Dependent Variable: Ln_DR_LTC_W

Model 3 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,388[a]	.150	.140	.048842094158660	.150	15.087	3	256	.000	2.067

a. Predictors: (Constant), EUR_W, DELTA_VOL_LTC_W, SG_LTC

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.048	.068		.702	.483	-.086	.181		
	SG_LTC	.945	12.483	.004	.076	.940	-23.636	25.527	.977	1.023
	DELTA_VOL_LTC_W	.034	.005	.385	6.618	.000	.024	.044	.979	1.022
	EUR_W	-.054	.076	-.041	-.712	.477	-.204	.096	.999	1.001

a. Dependent Variable: Ln_DR_LTC_W

Model 4 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,395[a]	.156	.136	.049028668554362	.156	7.783	6	252	.000	2.039

a. Predictors: (Constant), DELTA_VOL_LTC_W, DR_COMM_W, PRICE_NG_W, DR_SP500_W, SG_LTC, Ln_ATT_TOT

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.020	.087		-.232	.817	-.192	.151		
	PRICE_NG_W	.001	.019	.002	.034	.973	-.036	.037	.860	1.162
	Ln_ATT_TOT	.002	.005	.022	.348	.728	-.007	.011	.858	1.166
	DR_COMM_W	.116	.608	.011	.191	.849	-1.082	1.314	.971	1.030
	DR_SP500_W	1.069	.804	.078	1.330	.185	-.514	2.653	.973	1.028
	SG_LTC	.118	12.573	.001	.009	.992	-24.642	24.879	.972	1.029
	DELTA_VOL_LTC_W	.034	.005	.384	6.555	.000	.023	.044	.975	1.026

a. Dependent Variable: Ln_DR_LTC_W

Model 1 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,057[a]	.003	-.001	.041636231948384	.003	.835	2	515	.434	1.952

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	.051	.051		.997	.319	-.049	.150		
	PRICE_NG_W	.003	.004	.036	.806	.421	-.005	.012	.979	1.022
	EUR_W	-.064	.057	-.050	-1.117	.264	-.176	.048	.979	1.022

a. Dependent Variable: Ln_DR_LTC_W

Model 2 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,083[a]	.007	-.003	.041618572815997	.007	.713	5	514	.614	1.962

a. Predictors: (Constant), EUR_W, DR_SP500_W, SG_LTC, DR_COMM_W, Ln_ATT_TOT

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	-.039	.083		-.474	.636	-.203	.124		
	Ln_ATT_TOT	.004	.003	.072	1.326	.186	-.002	.009	.649	1.542
	DR_COMM_W	.217	.361	.027	.601	.548	-.492	.926	.935	1.069
	DR_SP500_W	.120	.381	.014	.314	.754	-.630	.869	.944	1.060
	SG_LTC	4.334	7.249	.026	.598	.550	-9.907	18.575	.998	1.002
	EUR_W	.003	.070	.002	.041	.968	-.135	.141	.644	1.553

a. Dependent Variable: Ln_DR_LTC_W

Model 3 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,302[a]	.091	.086	.039738190298121	.091	17.236	3	516	.000	2.026

a. Predictors: (Constant), EUR_W, DELTA_VOL_LTC_W, SG_LTC

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.045	.048		.942	.346	-.049	.140		
	SG_LTC	4.180	6.916	.025	.604	.546	-9.407	17.766	.999	1.001
	DELTA_VOL_LTC_W	.023	.003	.298	7.094	.000	.017	.029	1.000	1.000
	EUR_W	-.052	.054	-.041	-.973	.331	-.158	.053	.999	1.001

a. Dependent Variable: Ln_DR_LTC_W

Model 4 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,307[a]	.094	.082	.039889268092680	.094	7.560	7	510	.000	2.011

a. Predictors: (Constant), EUR_W, DR_SP500_W, DELTA_VOL_LTC_W, SG_LTC, PRICE_NG_W, DR_COMM_W, Ln_ATT_TOT

b. Dependent Variable: Ln_DR_LTC_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.017	.088		.192	.848	-.155	.189		
	PRICE_NG_W	.001	.005	.014	.273	.785	-.008	.011	.690	1.450
	Ln_ATT_TOT	.001	.003	.023	.360	.719	-.005	.008	.454	2.203
	DR_COMM_W	.168	.346	.021	.486	.627	-.512	.848	.935	1.070
	DR_SP500_W	.220	.366	.026	.600	.549	-.499	.939	.942	1.062
	SG_LTC	4.454	6.958	.027	.640	.522	-9.216	18.124	.996	1.004
	DELTA_VOL_LTC_W	.023	.003	.297	6.994	.000	.017	.029	.987	1.013
	EUR_W	-.038	.076	-.030	-.502	.616	-.188	.111	.504	1.984

a. Dependent Variable: Ln_DR_LTC_W

9.6.5 NEM

Model 1 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,082[a]	.007	-.001	.058790797642359	.007	.870	2	256	.420	2.125

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.034	.184		-.187	.852	-.396	.327		
	PRICE_NG_W	-.011	.009	-.092	-1.270	.205	-.029	.006	.738	1.355
	EUR_W	.074	.215	.025	.343	.732	-.350	.497	.738	1.355

a. Dependent Variable: Ln_DR_XEM_W

Model 2 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,151[a]	.023	-.004	.058812492686033	.023	.840	7	252	.555	2.164

a. Predictors: (Constant), CNY_W, DR_SP500_W, Ln_ATT_TOT, ATTENTION_REG, DR_COMM_W, ATTENTION_NEG, CURR

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.083	.266		-.313	.755	-.608	.441		
	CURR	-6.933E-05	.000	-.064	-.763	.446	.000	.000	.560	1.787
	DR_COMM_W	.236	.719	.022	.329	.743	-1.180	1.653	.891	1.122
	DR_SP500_W	-.109	.657	-.011	-.166	.868	-1.403	1.185	.913	1.096
	ATTENTION_NEG	-.001	.001	-.069	-1.039	.300	-.004	.001	.886	1.129
	ATTENTION_REG	.002	.002	.098	1.501	.135	-.001	.005	.914	1.094
	Ln_ATT_TOT	.021	.017	.083	1.294	.197	-.011	.054	.942	1.061
	CNY_W	-.011	.038	-.024	-.291	.771	-.087	.064	.549	1.822

a. Dependent Variable: Ln_DR_XEM_W

Model 3 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,225[a]	.050	.043	.057408708356993	.050	6.822	2	257	.001	2.146

a. Predictors: (Constant), CNY_W, DELTA_VOL_XEM_W

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	.220	.184		1.192	.234	-.143	.583		
	DELTA_VOL_XEM_W	.014	.004	.217	3.560	.000	.006	.021	.996	1.004
	CNY_W	-.033	.028	-.073	-1.194	.233	-.088	.022	.996	1.004

a. Dependent Variable: Ln_DR_XEM_W

Model 4 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,263[a]	.069	.035	.057714057362574	.069	2.050	9	249	.035	2.182

a. Predictors: (Constant), EUR_W, DR_SP500_W, Ln_ATT_TOT, DELTA_VOL_XEM_W, ATTENTION_REG, ATTENTION_NEG, DR_COMM_W, CURR, PRICE_NG_W

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	-.211	.269		-.785	.433	-.740	.318		
	CURR	6.560E-06	.000	.006	.054	.957	.000	.000	.302	3.313
	DR_COMM_W	.359	.707	.033	.508	.612	-1.034	1.753	.887	1.128
	DR_SP500_W	-.055	.644	-.005	-.086	.932	-1.325	1.214	.913	1.095
	ATTENTION_NEG	-.001	.001	-.070	-1.084	.279	-.003	.001	.894	1.118
	ATTENTION_REG	.002	.001	.085	1.335	.183	-.001	.005	.912	1.097
	Ln_ATT_TOT	.017	.016	.065	1.024	.307	-.015	.049	.940	1.064
	PRICE_NG_W	-.014	.015	-.118	-.949	.344	-.044	.015	.243	4.122
	DELTA_VOL_XEM_W	.013	.004	.210	3.402	.001	.006	.021	.979	1.021
	EUR_W	.096	.243	.033	.396	.692	-.383	.576	.554	1.805

a. Dependent Variable: Ln_DR_XEM_W

Model 1 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,026[a]	.001	-.007	.069258989834311	.001	.088	2	256	.916	1.860

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.003	.102		-.032	.975	-.205	.198		
	PRICE_NG_W	-.008	.027	-.022	-.313	.755	-.062	.045	.808	1.237
	EUR_W	.047	.120	.027	.388	.698	-.190	.284	.808	1.237

a. Dependent Variable: Ln_DR_XEM_W

Model 2 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,061[a]	.004	-.008	.069195564577263	.004	.317	3	256	.813	1.853

a. Predictors: (Constant), DR_SP500_W, Ln_ATT_TOT, DR_COMM_W

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.007	.064		-.109	.913	-.134	.120		
	Ln_ATT_TOT	.002	.006	.019	.309	.758	-.010	.014	.995	1.005
	DR_COMM_W	.772	.858	.057	.900	.369	-.917	2.461	.973	1.028
	DR_SP500_W	-.098	1.132	-.005	-.087	.931	-2.328	2.132	.977	1.023

a. Dependent Variable: Ln_DR_XEM_W

Model 3 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,416[a]	.173	.167	.062902525768531	.173	26.968	2	257	.000	1.970

a. Predictors: (Constant), EUR_W, DELTA_VOL_XEM_W

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.007	.087		-.083	.934	-.179	.164		
	DELTA_VOL_XEM_W	.039	.005	.416	7.335	.000	.029	.050	.999	1.001
	EUR_W	.014	.098	.008	.139	.890	-.180	.207	.999	1.001

a. Dependent Variable: Ln_DR_XEM_W

Model 4 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,422[a]	.178	.161	.063196468398548	.178	10.937	5	253	.000	1.973

a. Predictors: (Constant), DELTA_VOL_XEM_W, Ln_ATT_TOT, DR_SP500_W, DR_COMM_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.022	.112		.200	.841	-.199	.244		
	PRICE_NG_W	-.008	.024	-.021	-.348	.728	-.055	.039	.861	1.162
	Ln_ATT_TOT	.001	.006	.007	.119	.905	-.011	.012	.858	1.165
	DR_COMM_W	.465	.784	.034	.593	.554	-1.079	2.010	.970	1.031
	DR_SP500_W	-.602	1.037	-.034	-.580	.562	-2.643	1.440	.973	1.028
	DELTA_VOL_XEM_W	.039	.005	.419	7.315	.000	.029	.050	.989	1.011

a. Dependent Variable: Ln_DR_XEM_W

Model 1 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,013[a]	.000	-.004	.064310663818944	.000	.043	2	515	.957	1.956

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.031	.078		.398	.691	-.123	.185		
	PRICE_NG_W	.000	.007	-.003	-.060	.952	-.013	.013	.979	1.022
	EUR_W	-.024	.088	-.012	-.277	.782	-.197	.149	.979	1.022

a. Dependent Variable: Ln_DR_XEM_W

Model 2 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,094[a]	.009	.001	.064079155857054	.009	1.155	4	515	.330	1.972

a. Predictors: (Constant), EUR_W, DR_SP500_W, DR_COMM_W, Ln_ATT_TOT

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.176	.128		-1.375	.170	-.427	.075		
	Ln_ATT_TOT	.009	.004	.105	1.936	.053	.000	.017	.649	1.540
	DR_COMM_W	.547	.556	.045	.984	.325	-.545	1.639	.935	1.069
	DR_SP500_W	-.129	.587	-.010	-.220	.826	-1.283	1.024	.944	1.059
	EUR_W	.110	.108	.056	1.018	.309	-.102	.322	.644	1.553

a. Dependent Variable: Ln_DR_XEM_W

Model 3 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,300[a]	.090	.087	.061274733593380	.090	25.636	2	517	.000	1.994

a. Predictors: (Constant), EUR_W, DELTA_VOL_XEM_W

b. Dependent Variable: Ln_DR_XEM_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.048	.074		.643	.521	-.098	.194		
	DELTA_VOL_XEM_W	.023	.003	.301	7.156	.000	.017	.029	.998	1.002
	EUR_W	-.051	.083	-.026	-.610	.542	-.213	.112	.998	1.002

a. Dependent Variable: Ln_DR_XEM_W

Model 4 – 2016-2017

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.219	6	.036	9.752	,000[b]
	Residual	1.911	511	.004		
	Total	2.130	517			

a. Dependent Variable: Ln_DR_XEM_W

b. Predictors: (Constant), EUR_W, DR_SP500_W, DELTA_VOL_XEM_W, PRICE_NG_W, DR_COMM_W, Ln_ATT_TOT

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.215	.134		-1.606	.109	-.479	.048		
	PRICE_NG_W	-.010	.007	-.069	-1.360	.174	-.025	.005	.691	1.447
	Ln_ATT_TOT	.012	.005	.145	2.344	.019	.002	.022	.458	2.182
	DR_COMM_W	.587	.531	.048	1.106	.269	-.456	1.630	.935	1.069
	DR_SP500_W	-.130	.560	-.010	-.231	.817	-1.231	.972	.944	1.059
	DELTA_VOL_XEM_W	.023	.003	.302	7.203	.000	.017	.029	.997	1.003
	EUR_W	.143	.116	.072	1.226	.221	-.086	.372	.505	1.979

a. Dependent Variable: Ln_DR_XEM_W

9.6.6 Cryptocurrency weekly

Model 1 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,334[a]	.112	.076	.083299058440776	.112	3.086	2	49	.055	2.237

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.498	.568		-.877	.385	-1.640	.644		
	PRICE_NG_W	-.070	.028	-.388	-2.482	.017	-.126	-.013	.741	1.350
	EUR_W	.784	.665	.184	1.178	.244	-.553	2.121	.741	1.350

a. Dependent Variable: WR_CC_Ln_W

Model 2 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,614[a]	.377	.261	.074494270257498	.377	3.248	8	43	.006	2.129

a. Predictors: (Constant), EUR_W, PUBLICITY_REG, SG_CRYPTO_Ln, PUBLICITY_TOT_Ln, WR_SP500_W, PUBLICITY_NEG, WR_COMM_W, CURR
b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.651	.741		.878	.385	-.845	2.146		
	CURR	.000	.000	-.303	-2.245	.030	-.001	.000	.795	1.258
	WR_COMM_W	1.255	.859	.197	1.460	.152	-.478	2.988	.800	1.250
	WR_SP500_W	-2.816	.926	-.406	-3.042	.004	-4.683	-.949	.813	1.230
	PUBLICITY_NEG	-.003	.003	-.127	-.975	.335	-.010	.004	.851	1.175
	PUBLICITY_REG	-.003	.004	-.093	-.714	.479	-.012	.006	.856	1.169
	PUBLICITY_TOT_Ln	-.100	.068	-.190	-1.476	.147	-.236	.037	.872	1.147
	SG_CRYPTO_Ln	8.861	15.285	.075	.580	.565	-21.964	39.686	.868	1.153
	EUR_W	.683	.538	.161	1.268	.212	-.403	1.769	.905	1.105

a. Dependent Variable: WR_CC_Ln_W

Model 3 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,433[a]	.187	.136	.080510678334696	.187	3.687	3	48	.018	2.288

a. Predictors: (Constant), EUR_W, W_LIQ_CC_Ln_W, SG_CRYPTO_Ln

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.136	.509		.268	.790	-.888	1.160		
	SG_CRYPTO_Ln	12.759	15.595	.108	.818	.417	-18.597	44.116	.973	1.027
	W_LIQ_CC_Ln_W	.059	.019	.409	3.112	.003	.021	.098	.980	1.020
	EUR_W	-.153	.560	-.036	-.273	.786	-1.280	.974	.976	1.025

a. Dependent Variable: WR_CC_Ln_W

Model 4 – 2016

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,673[a]	.452	.335	.070649289140394	.452	3.855	9	42	.001	2.149

a. Predictors: (Constant), W_LIQ_CC_Ln_W, PUBLICITY_TOT_Ln, SG_CRYPTO_Ln, PUBLICITY_REG, EUR_W, WR_COMM_W, PUBLICITY_NEG, WR_SP500_W, PRICE_NG_W

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.225	.780		.289	.774	-1.349	1.799		
	WR_COMM_W	1.321	.818	.207	1.616	.114	-.329	2.971	.795	1.258
	WR_SP500_W	-2.736	.897	-.395	-3.051	.004	-4.547	-.926	.779	1.284
	PUBLICITY_NEG	-.002	.003	-.097	-.777	.442	-.009	.004	.842	1.188
	PUBLICITY_REG	-.004	.004	-.117	-.955	.345	-.012	.004	.870	1.150
	PUBLICITY_TOT_Ln	-.103	.064	-.196	-1.603	.116	-.232	.027	.872	1.147
	SG_CRYPTO_Ln	8.154	14.409	.069	.566	.574	-20.924	37.233	.878	1.139
	EUR_W	1.005	.589	.236	1.706	.095	-.184	2.193	.680	1.470
	PRICE_NG_W	-.051	.026	-.287	-1.972	.055	-.104	.001	.616	1.624
	W_LIQ_CC_Ln_W	.044	.017	.304	2.532	.015	.009	.079	.904	1.107

a. Dependent Variable: WR_CC_Ln_W

Model 1 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,115[a]	.013	-.027	############	.013	.328	2	49	.722	1.305

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.231	.405		-.569	.572	-1.046	.584		
	PRICE_NG_W	.009	.109	.013	.086	.932	-.210	.228	.817	1.223
	EUR_W	.324	.469	.109	.691	.493	-.618	1.267	.817	1.223

a. Dependent Variable: WR_CC_Ln_W

Model 2 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,380[a]	.145	.072	############	.145	1.986	4	47	.112	1.313

a. Predictors: (Constant), SG_CRYPTO_Ln, WR_COMM_W, WR_SP500_W, PUBLICITY_NEG

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.008	.039		-.210	.834	-.086	.070		
	WR_COMM_W	-2.235	2.189	-.138	-1.021	.312	-6.638	2.168	.999	1.001
	WR_SP500_W	.355	2.157	.022	.165	.870	-3.984	4.695	.977	1.023
	PUBLICITY_NEG	.001	.001	.240	1.705	.095	.000	.002	.921	1.085
	SG_CRYPTO_Ln	50.848	21.504	.333	2.365	.022	7.587	94.109	.915	1.093

a. Dependent Variable: WR_CC_Ln_W

Model 3 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,563[a]	.317	.274	############	.317	7.414	3	48	.000	1.444

a. Predictors: (Constant), EUR_W, W_LIQ_CC_Ln_W, SG_CRYPTO_Ln

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.135	.337		.401	.690	-.543	.814		
	SG_CRYPTO_Ln	48.017	19.924	.315	2.410	.020	7.957	88.076	.834	1.199
	W_LIQ_CC_Ln_W	.091	.022	.496	4.132	.000	.047	.135	.986	1.014
	EUR_W	-.154	.391	-.051	-.393	.696	-.940	.633	.830	1.204

a. Dependent Variable: WR_CC_Ln_W

Model 4 – 2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,620[a]	.385	.303	.100922029823553	.385	4.692	6	45	.001	1.488

a. Predictors: (Constant), W_LIQ_CC_Ln_W, PRICE_NG_W, WR_SP500_W, WR_COMM_W, SG_CRYPTO_Ln, PUBLICITY_NEG
b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	-.212	.292		-.724	.473	-.801	.377		
	WR_COMM_W	-.866	1.925	-.053	-.450	.655	-4.743	3.010	.971	1.030
	WR_SP500_W	.878	1.874	.056	.469	.642	-2.897	4.654	.972	1.029
	PUBLICITY_NEG	.001	.001	.293	2.171	.035	.000	.003	.750	1.333
	SG_CRYPTO_Ln	51.622	19.325	.339	2.671	.010	12.699	90.545	.851	1.175
	PRICE_NG_W	.056	.096	.081	.583	.563	-.137	.249	.716	1.397
	W_LIQ_CC_Ln_W	.091	.022	.495	4.155	.000	.047	.135	.964	1.037

a. Dependent Variable: WR_CC_Ln_W

Model 1 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,019[a]	.000	-.019	.108877590954713	.000	.019	2	101	.981	1.446

a. Predictors: (Constant), EUR_W, PRICE_NG_W

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	.015	.293		.052	.958	-.566	.597		
	PRICE_NG_W	.003	.025	.014	.137	.892	-.046	.053	.980	1.020
	EUR_W	.038	.329	.012	.117	.907	-.614	.691	.980	1.020

a. Dependent Variable: WR_CC_Ln_W

Model 2 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,353[a]	.124	.089	.102917976384427	.124	3.519	4	99	.010	1.579

a. Predictors: (Constant), SG_CRYPTO_Ln, WR_SP500_W, PUBLICITY_NEG, WR_COMM_W

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95,0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	-.007	.024		-.295	.768	-.055	.041		
	WR_COMM_W	.057	.969	.006	.058	.954	-1.865	1.978	.923	1.083
	WR_SP500_W	-1.727	1.022	-.165	-1.689	.094	-3.756	.302	.924	1.082
	PUBLICITY_NEG	.001	.000	.267	2.730	.007	.000	.002	.927	1.078
	SG_CRYPTO_Ln	37.194	13.853	.266	2.685	.009	9.707	64.682	.904	1.106

a. Dependent Variable: WR_CC_Ln_W

Model 3 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,476[a]	.227	.203	.096244692708581	.227	9.767	3	100	.000	1.601

a. Predictors: (Constant), EUR_W, W_LIQ_CC_Ln_W, SG_CRYPTO_Ln

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	.194	.263		.736	.463	-.328	.716		
	SG_CRYPTO_Ln	25.608	12.744	.183	2.009	.047	.325	50.892	.934	1.070
	W_LIQ_CC_Ln_W	.076	.015	.443	5.029	.000	.046	.106	.995	1.005
	EUR_W	-.214	.299	-.065	-.715	.476	-.806	.379	.930	1.076

a. Dependent Variable: WR_CC_Ln_W

Model 4 – 2016-2017

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,554[a]	.307	.264	.092484466050105	.307	7.172	6	97	.000	1.715

a. Predictors: (Constant), W_LIQ_CC_Ln_W, PRICE_NG_W, SG_CRYPTO_Ln, WR_SP500_W, WR_COMM_W, PUBLICITY_NEG

b. Dependent Variable: WR_CC_Ln_W

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	Upper Bound	Collinearity Statistics Tolerance	VIF
1	(Constant)	-.023	.064		-.360	.720	-.151	.104		
	WR_COMM_W	.383	.880	.039	.435	.665	-1.363	2.129	.904	1.106
	WR_SP500_W	-1.251	.924	-.120	-1.354	.179	-3.085	.582	.914	1.095
	PUBLICITY_NEG	.001	.000	.274	3.080	.003	.000	.002	.900	1.111
	SG_CRYPTO_Ln	34.959	12.474	.250	2.802	.006	10.200	59.717	.900	1.111
	PRICE_NG_W	-.001	.022	-.005	-.061	.951	-.044	.042	.938	1.066
	W_LIQ_CC_Ln_W	.074	.015	.432	5.056	.000	.045	.104	.978	1.022

a. Dependent Variable: WR_CC_Ln_W