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FACTORS EXPLAINING PRICE DYNAMICS OF CRYPTO ASSETS

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I hereby declare that I have compiled the thesis independently
and all works, important standpoints and data by other authors
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has not been previously presented for grading.
The document length is 10585 words from the introduction to the end of conclusion.

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ABSTRACT

In 2009 the world of finance welcomed Bitcoin as a new financial instrument. Now over 10 years later there are numerous different crypto assets in the market that have amazed people with their extremely high price fluctuations and volatility. Previous studies on the crypto assets have indicated that these assets are speculative assets and that the market of cryptocurrencies is inefficient and used for short-term trading. Using different analysis methods, this paper analyses the price dynamics of Bitcoin, Ethereum and Ripple in the time period of 2018-2019. The results concluded in this paper are in line with the results and indications of previous studies.

Keywords: Crypto assets, volatility, trends, day of the week effect

INTRODUCTION

The term cryptocurrency has been a growing trend in our world over the past decade. In the finance environment cryptocurrency has been seen as new financial instrument, even though it has existed now over 10 years with the creation of the Bitcoin in the start of year 2009. Ever since 2009, the market of cryptocurrency has expanded enormously and the knowledge and popularity of this financial instrument has increased.

As being a new instrument in financial world, there is still a lot that we do not know about the cryptocurrency. In the end of 2017, there was a huge rise in the price of Bitcoin. People who had bought Bitcoin in the beginning of that year for $900 had received close to 2000 percent return on their investment when Bitcoin surged up to almost $20000 on the 17th December of 2017. During the next couple of days Bitcoin had a decline in price of 30 percent of its value (Kelly, Chavez-Dreyfuss, 2017).

Volatility of the cryptocurrency can make investors insecure, but as the past has shown on Bitcoin's example then investors can earn huge rewards. This paper tries to explain what impacts and affects the price of the cryptocurrency and its market, because it has been very volatile and unpredictable on the first glance.

The aim of this thesis is to understand through statistical analysis how the cryptocurrency has behaved in the past and trying to predict how it can be used for investors' advantage in the future. Furthermore, links between the cryptocurrencies and other asset classes will be analysed.

Research questions addressed in this paper are following:

1) What explains the price dynamics of the cryptocurrencies?

2) Can crypto assets be used as safe haven assets?

3) Is there any "best" or "worst" weekdays for trading crypto assets, which may serve as a lasting evidence about market inefficiency?

The structure of the thesis is sectioned into three main parts, which have sub-sections as well. In the first part of the thesis the characteristics of the crypto assets will be discussed in order to understand this financial asset. Additionally, a more in-depth look on the previous empirical studies on the topic will be discussed and finally an overview of the market of the cryptocurrencies will be analysed. The second part of the paper will explain the methodology and data used in this thesis. In the third part of the thesis, a correlation analysis and volatility calculations of the asset classes will be conducted. Additionally, the day of the week effect will be analysed and finally a regression analysis will be conducted.

Finally, the author would like to thank his supervisor Peeter Luikmel for his guidance throughout the writing process of the paper and mentor Andres Kitter for insights on the topic.

1. LITERATURE REVIEW

The following section will cover the theoretical framework of cryptocurrencies and its market and the main components that can affect the price of the crypto assets. The theoretical framework for this paper was conducted by gathering information from other academic papers, articles, published books and other reliable online resources.

1.1 Cryptocurrency

Understanding of the term cryptocurrency is key for this paper. The idea of cryptocurrency has been developed almost 40 years since 1980s when this concept was firstly getting developed and researched. Cryptocurrency, in short, is a virtual currency very much similar to the standard currency, which allows a person to pay for goods and services virtually with an exception of not depending on the institution of monetary authority (Farell, 2015). This means that cryptocurrencies are not affected by the decisions of monetary institutions, because they are limited in supply, which means that there is certain amount of coins in circulation and the coins used in transactions keep the users anonymous (Lansky, 2018).

Cryptocurrency, however, is not a regular currency or regular fiat money. It is worth mentioning that central bankers prefer the term crypto assets over cryptocurrency, because the crypto assets do not have an issuer like central bank currencies have. First, we have to understand how fiat money works and what gives it its value. Fiat money is a government-issued currency that does not hold intrinsic value. Simply put it is a piece of paper that is issued and controlled by a central authority. This is why fiat currencies are called as centralised currencies because their value comes from the actions of central authorities. Central authorities, however, hold the power of fiat money, because of the value of a fiat currency is related to supply and demand theory and that is what gives fiat currency its value (Investopedia 2020).

There is still a lot of debate going on what cryptocurrency is. Some people say it is a currency and some people consider it as a commodity. However, Gronwald (2019), has examined Bitcoin's characteristics and when looking into the volatility of the Bitcoin comparing it to the crude oil and gold then Bitcoin can be referred to as a commodity. One of the characteristics of commodities is that they are volatile and they are good hedging assets (Hecht, 2020). This debate has been seen as very controversial, because of Jin *et. al* (2019) who concluded that crude oil and gold have been used throughout the long periods as hedging assets. Additionally, they found out that Bitcoin, however, as a new financial class has no intrinsic value compared to the commodities like gold and crude oil and thus Bitcoin's price does not have a strong effect on the commodity market as gold has. Even though, Bitcoin does not have such a strong effect on the commodity market, Jin *et. al* (2019) stated in their study that it can still act as hedging asset.

Cryptocurrencies relate both to the commodities and to the regular currency. They are something in between. Because they are not physical commodities they are valued a little bit differently. Fiat currency has value because people trust central authorities and perceive that a piece of paper has value. These central authorities can be trusted, because the issuers of the currencies have balance sheets where issued currencies are covered by assets. Contrary to that crypto assets get their value from their usefulness and scarcity. Different cryptocurrencies have different utilities and applications. For example, with Bitcoin, people can nowadays buy plane tickets and it acts as a medium of exchange. The utility side of cryptocurrency is still very new because cryptocurrency as such itself is quite new to the world, but with the improvement of technology and implementation of new ideas cryptocurrency's technology can play a significant role in the future. Scarcity, however, is another factor that can influence the price of crypto assets because if we take look at Bitcoin again then there is only a certain amount of Bitcoin in supply, which factors a lot in its price (DeMartino, 2016).

Unlike fiat money, cryptocurrency is backed by its code, which means that it is a decentralised currency. Everybody who wants to be part of it can be part of it and all of the members of this society have equal benefits in this system. This is the uniqueness of Bitcoin and other decentralised systems that there is not an organization that controls it. With a fiat currency, the central governing body has the power to print more money and thus create inflation. With inflation, the value of the currency will decrease. Even though with decentralized currencies there is no administrative body that can have such a power, there are flaws that can affect the price of the cryptocurrency as well. For example, people can lose access codes to their virtual wallets where they keep their cryptocurrencies and never get access to their coins. This term is called deflation. As we know there is a certain amount of Bitcoin supply, which makes this currency very scarce and when people lose their access to their coins then nobody can get this access back and these coins can be written off from the supply, which means the currency itself becomes even more scarce and the one coin will become even more valuable (Hosp, 2017).

Another factor on the price of the cryptocurrency is the relationship between the utility and speculative value. Less established crypto assets have higher speculative value, which means they are riskier assets. Investors usually invest in these assets when they see good development team behind these crypto assets and see the potential in growth. More established cryptocurrencies like Bitcoin, Ethereum and Ripple, they have higher utility value because these currencies have either better usefulness or more applications, meaning their potential is lower (Burniske, Tatar, 2018).

Cryptocurrency has a unique ecosystem. The whole ecosystem is not physical, but all of the components are virtual. Most people see the cryptocurrency as a network, distributed ledger or just a blockchain technology (DeMartino, 2016). All of it is true because they all are the pieces in the ecosystem, but how does the ecosystem process work? Crypto assets can be defined as cryptographically secured assets that have digital value or contractual rights, which can be transferred, stored or traded in the electronic system (FCA, 2019). Blockchain technology has an enormous significance in the whole cryptocurrency ecosystem. Blockchain technology has made the market and its investors anonymous, and it also has a security function. There is a synonym to the blockchain, in other words, it is called a distributed public ledger. Every person who owns Bitcoins, for example, have their wallet, which can be tracked in the blockchain but its owners remain anonymous in the system. In this distributed ledger system people can make exchanges and transactions without the fee. In order for the transaction to be verified cryptographically, there are people called miners who process the transactions by solving the computational mathematical problems in the blockchain technology (DeMartino, 2016).

The blockchain technology has created many options and functions for the cryptocurrencies. People can now raise capital through initial coin offerings (ICO), which is equivalent to the initial public offering (IPO). ICO's are used mainly for capital raising, especially in start-up companies, where the issuer of a start-up company offers their cryptocurrency in exchange for more stable cryptocurrency like Bitcoin or Ethereum, or regular fiat currency (Frankenfield, 2019).

1.2 Previous empirical studies on the topic

From an economic perspective, crypto assets are seen similar to fiat currencies, because both have similar factors that drive their price and volatility, and both are used for the same purposes. However, cryptocurrencies have more different applications than fiat currencies. Ciaian *et. al* (2016) looked into the price formation of the Bitcoin. In their paper, there was evidence that Bitcoin is affected by the market's forces of supply and demand. Furthermore, in their work, they found evidence that Bitcoin's demand is stronger determinant in price formation because the supply of the Bitcoin will become limited in the future once the last Bitcoin is mined. Once the last Bitcoin is mined, which is expected to be in the year 2140, then only the demand side can affect the price changes. Additionally, they pointed out that supply and demand influenced the price more in the later years of Bitcoin's emergence because Bitcoin became established currency in the market. As the time passes on the algorithm of Bitcoin will get more complex and the mining of the coin will become harder. This impacts the supply of the Bitcoin and affects its price even before the last Bitcoin will be mined.

Price formation of Bitcoin was researched by Kristoufek (2015) as well. He conducted more extensive but wider research by looking into the Bitcoin price dynamics through sources of price movements while taking into account fundamental and technical aspects, and the characteristic of being a speculative asset. Speculation, in the world of finance, refers to the transaction that has a substantial risk involved in the transaction. However, with the higher risk there is possibility for a higher return. Investors who trade with speculative assets tend to look at the price fluctuations and focus on the short-term profits. Speculative assets mostly are held for shorter period of time (Farley, 2019). It was concluded in the Kristoufek (2015)'s study that the price dynamics are affected by three main things. Firstly, Bitcoin is used as a speculative asset, which means that standard fundamental factors like usage in trade, money supply and price level affect the price of the Bitcoin in the long term. However, there have been controversies when considering fundamental factors on the price of the Bitcoin. Baek & Elbeck (2015) compared Bitcoin's daily returns against S&P500 index and concluded that Bitcoin was in the period of the 19th of July 2010 - the 19th of July of 2013 26 times more volatile than S&P500. Authors looked into the Bitcoin's market returns, and their regression results suggested that Bitcoin returns are internally driven by buyers and sellers and is not affected by fundamental economic factors. Kristoufek (2015) additionally analysed Bitcoin from a technical perspective, it was concluded that the increasing price of a Bitcoin motivates people to become miners. It was pointed out that this motivation will diminish in the future because mining will become more expensive in the latter stages of Bitcoin mining in the blockchain (Kristoufek, 2015).

Mining is a vital process through what, cryptocurrencies that are mineable can be acquired. This process also confirms the transactions of crypto assets in blockchain technology. Everybody who has a computer can become a miner because mining needs computational power, which comes from the computers' GPU. When the crypto assets increase in price, it attracts more people to start mining. With the higher competition in the mining ecosystem, it gives miners a bigger chance to earn the same crypto tokens they are mining. With the price growth of an asset more people will be attracted to try mining and with more people mining in the blockchain technology more secure the cryptocurrency network will be (Burniske, Tatar, 2018.)

Internet and attention can lead to the price changes of financial assets. Choi and Varian (2012) researched if Google trends can predict the present. Authors concluded that there is a correlation to the google searches and travel destinations.

Based on Choi and Varian (2012)'s findings, there have been numerous studies on the attention or social media impact on the prices of the crypto assets. Urquhart (2016) studied the inefficiency of the market on Bitcoin's example and though research concluded that Bitcoin was strongly inefficient, the author stated that when cryptocurrency becomes more established in the market, then its returns are easier to predict. Urquhart (2016)'s findings can be linked to Caporale *et. al* (2018)'s study, which looked at the persistence levels of most established crypto assets like Bitcoin, Litecoin, Dash and Ripple throughout the years of 2013-2017. Authors concluded that market was still inefficient but had become less inefficient over the time period. The persistence level, which is also considered as predictability, shows that trend trading can be used to generate abnormal returns in the cryptocurrency market.

Trend trading was studied by Urquhart (2018) as well. The author studied the Google trends effect on Bitcoin. Urquhart (2018) used Google Trends data from the period of 1st August 2010 to 31st July 2017. Author's findings suggested that Bitcoin's previous day's volatility and volume have an effect on the increase of Google Trends keywords related to the Bitcoin. These findings are directly linked with Shen *et. al* (2019) findings where the authors looked into the correlation between the number of Twitter tweets about Bitcoin and realized volatility and returns. Authors found that a number of previous day tweets are significant drivers of Bitcoin volatility and volume, but not correlated with the asset returns.

Cryptocurrency market volatility is very high and unpredictable, which is the reason why people are trying to use crypto assets for short-term trading and find an advantage in this market. One of the papers by Caporale and Plastun (2019), looked into the day of the week effect in crypto assets. Day of the week effect analyses if there are any anomalies during the certain days of the week, where prices can increase or decrease abnormally. These anomalies should not happen in the efficient market. In that paper, they studied ten different cryptocurrencies from 2013 to 2017 and ran a series of statistical tests to find if there are any anomalies relating to the crypto assets studied and the weekdays. From all the different tests, only Bitcoin had anomalies confirmed by different testing methods on Mondays. Researchers concluded the study by stating that only Bitcoin, which is the most dominant currency in the market, has anomaly on Mondays, where there are abnormal positive returns on that day. Caporale and Plastun (2019) also ran a trading simulation approach using that finding for their advantage and concluded that Bitcoin generated 60% of returns on Mondays during the sample period of 2013-2017. However, when looking at the years individually, the returns are lower (Caporale, Plastun, 2019).

A different approach was taken by Grobys *et. al* (2020) who studied the technical trading aspect of cryptocurrency. They looked into the variable moving average strategy and the effect of the simple moving average trading strategies in the cryptocurrency market between the start of 2016 and the end of 2018. Opposite to the other scientific papers conducted on the crypto assets matter, they decided to focus more on the other cryptocurrencies than Bitcoin. Their approach was to look at different simple moving averages based on historical daily prices. They conducted empirical studies where they applied 20-day, 50-day, 100-day and 150-day simple moving average trading strategies and used them for the variable moving average. Grobys *et. al* (2020) concluded that the variable moving average strategy provides significant profits in the crypto markets when used 20-day simple moving average data. They also pointed out that it is the opposite approach to stock market trading, where moving average data used is longer.

Tzouvanas *et. al* (2019) studied cryptocurrency momentum trading. They looked at the 12 different crypto assets that had the largest market capitalization in the 3-year time period and used the daily price data. Tzouvanas *et. al* (2019) found out that positive returns are possible while using momentum trading approach, but only in short-term. Additionally, they concluded that their findings support the idea that the cryptocurrency market is inefficient in the short-term and efficient in the long run. Lastly, their research concluded that there was a lower correlation in the momentum portfolio which had traditional assets and crypto assets compared to the portfolio with only traditional assets, which means that investors should consider crypto assets as a risk diversification option (Tzouvanas *et. al* 2019).

The empirical studies that have studied the price dynamics and technical aspects of the crypto assets have very strong beliefs that cryptocurrencies are very volatile and unpredictable compared to stock markets and safe haven commodity gold. Previous papers have concluded that volatility the difference of volatility between cryptocurrencies and stock markets is very huge (Baek & Elbeck, 2015). Additionally, there seems to be a positive link in short-term trading strategies and crypto assets (Grobys *et. al* 2020).

Based on the information on the previous literature, it can be concluded that crypto assets can be speculative assets, because of their high volatility and short-term trading preference.

1.3 Cryptocurrency market

With the emergence of the Bitcoin the crypto market started pushing towards the future and ever since the market has expanded significantly. At the time of writing this there are 5109 different cryptocurrencies with the total market capitalization of $301,650,620,224 (CoinMarketCap, 2020). As for market itself, cryptocurrency market can be seen as hugely volatile. Numerous papers have been conducted on understanding the volatility of the cryptocurrency market and cryptocurrency prices. Ciaian *et. al* (2016) examined the reasons behind the price fluctuations and the volatility of the cryptocurrencies. They found that supply and demand have huge impact on the price of the Bitcoin, because the supply of the Bitcoin is limited, thus it has an effect on the price. Additionally, Urquhart (2016) studied the cryptocurrency market and has stated that the market in the earlier years showed strong inefficiency, but in later years it has improved. However, Wei (2018) has found that when the market efficiency is stronger, the volatility is lower. Additionally, Wei (2018) examined the market situation couple of years later than Urquhart (2016) and found out that Bitcoin and other established currencies have become more efficient in terms of market efficiency, but with constant emergence of new cryptocurrencies it is hard to predict their price and behaviour. This means that more established cryptocurrencies that have a bigger market capitalization are easier to predict.

Figure 1 describes the volatility of the cryptocurrency market capitalization.

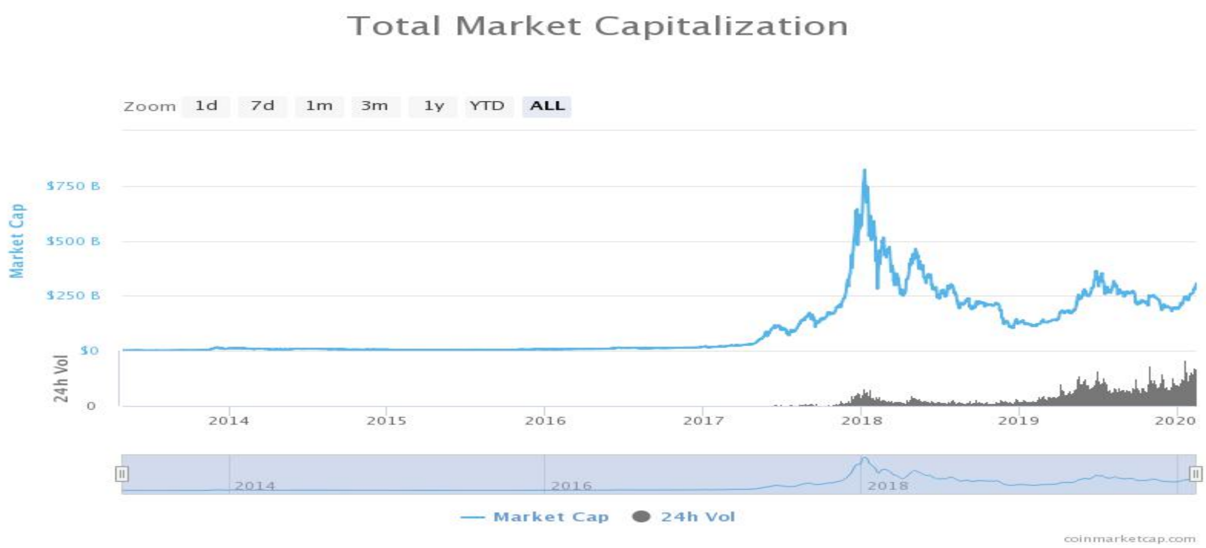

Figure 1. Total Market Capitalization
Source: CoinMarketCap (2020.1)

As Figure 1 demonstrates that cryptocurrency market is very volatile, which was concluded by Aalborg *et. al* (2019) as well. Furthermore, their study points out that volatility in the crypto market is high and in correlation with daily trading volume.

1.3.1 Market overview

It was in the January of 2009 when the first cryptocurrency was published to the market. The currency we are talking about is Bitcoin, which was created by the guy called Satoshi Nakamoto, which is pseudonym of a person or a group of people who created Bitcoin. Satoshi created the first ever successful decentralized cryptocurrency (Nakamoto, 2008). At the time of writing this, Bitcoin is number one virtual currency on the market. By being the first virtual currency and creating the phenomenon of cryptocurrency market, Bitcoin is the most established virtual currency with the total market capitalization of $178,482,530,272, which is little over than 63% of the whole market capitalization. Currently, there is 18,221,787 (BTC) in circulation and the maximum supply for the Bitcoin is 21,000,000 (BTC) (CoinMarketCap, 2020.2). A huge part of the market is influenced on the Bitcoin's behaviour, because it is the most popular with the highest market capitalization.

Ethereum is another virtual currency that has established their position in the market. Ethereum was launched in 2015 and the creator of this virtual currency is Vitalik Buterin. Main core aspects, like being decentralized currency and offering anonymity in transactions, of Ethereum is similar to the Bitcoin, but the most significant difference is that Ethereum is programmable and script-based cryptocurrency, which allows the creators to create applications as well. Therefore, we can state that Ethereum currency is virtual money in Ethereum network where people can use Ether for creating applications in Ethereum system (Ethereum, 2020). At the time of writing this, Ethereum's market capitalization is $27,594,707,997 and there is 109,735,487 Ether (ETH) of supply circulating on the market. This makes the price of one Ether to be $257.47 (CoinMarketCap 2020.2).

Currently the 3rd best-established cryptocurrency on the market. The Ripple was founded in 2012. Unlike other established cryptocurrencies, Ripple does not use miners for creating supply and transactions. Ripple's application is towards making speedy transactions. Like Bitcoin, the transactions are fast and not that costly as they are through a centralized system (Burniske, Tatar, 2018). At the moment Ripple has a market capitalization of $10,671,718,950 (USD) and there is currently in circulation 43,818,008,717 (XRP). Ripple is not that scarce cryptocurrency. The total supply can lead up to 100,000,000,000 (XRP). At the time of writing this, the cost of one Ripple coin (XRP) is $0.243324 (USD) (CoinMarketCap, 2020.3).

Litecoin is the 7th most established cryptocurrency on the market. Litecoin was founded in 2011 and technically it is very similar to Bitcoin. The key differences between Bitcoin and Litecoin are that Litecoin has faster transaction speed and it is cheaper to use (CoinMarketCap, 2020.3). Currently, Litecoin has a total market capitalization of $3,993,583,357 (USD). Circulating supply of Litecoin is at the moment 64,233,025 (LTC), this makes one Litecoin to be worth of $62.20 (USD). The maximum supply of the Litecoin can increase up to 84,000,000 (LTC) (Cointelegraph, 2020).

The 12th rank in the list of market capitalization is held by a cryptocurrency called Chainlink. Chainlink was founded in 2014. Chainlink provides an open-source smart contract technology (Partz, 2020). Smart contract technology offers people a way to exchange money, property or shares without the need of notary or a lawyer. Smart contracts are legally binding and enforce the obligations of the contract immediately as regular binding contracts (Rosic, 2017). Currently, Chainlink has a total market capitalization of $912,444,854 (USD). The total supply of Chainlink coins can reach to 1,000,000,000 (LINK). At the moment the circulating supply of Chainlink is 350,000,000 (LINK) and one (LINK) is priced at $2.6 (CoinMarketCap, 2020.3).

Dash is in the list of market capitalization at the 20th spot. Dash was created in 2014 by the guy called Evan Duffield, who was fascinated by the Bitcoin and decided to create his and similar cryptocurrency (Rosic, 2018). Dash has similar functions like Bitcoin. Dash is mainly used as a medium of exchange, which means it is used for shopping, paying bills or paying salaries (Dash, 2020). The market capitalization of the Dash is $490,143,153 (USD). Currently, there is 9,377,239 (DASH) in circulation, which makes one (DASH) coin worth $52.42 (USD). The maximum supply can reach up to the 18,900,000 (DASH) (CoinMarketCap, 2020.3)

Steem is a crypto asset that is built for social and content-based blockchain applications like Steemit (Coinbase, 2020). Steemit is an application where people can create and provide content and earn through quality content Steem coins (Steem, 2020). Steem has a market capitalization of $46,327,015 (USD) and the circulating supply is 362,219,158 (STEEM), which makes one Steem coin worth $0.127898 (USD). Total supply of Steem coin can increase up to 379,193,252 (STEEM) through the process of mining (CoinMarketCap, 2020.3)

Horizen is a crypto asset that provides its users with a platform that is designated for private communication and financial activities. This platform gives its users and companies a way to make daily private transactions, exchange messages and release applications in their decentralized system (SimpleSwap, 2020). At the time of writing this, the market capitalization of Horizen is

$48,343,362 (USD), and there is 8,618,388 (ZEN) of supply in circulation. This makes one ZEN worth to be $5.61 (USD). The total supply of the Horizen coins can increase up to 21,000,000 (ZEN) (CoinMarketCap 2020.3).

2. DATA & METHODOLOGY

2.1. Data

The first step was to determine what kind of data to use in analysis part of the thesis. Complementarily to scientific studies mentioned in the literature review on the crypto assets, this paper has a broader perspective on the price dynamics of the cryptocurrencies. The data used in the empirical section refers to the time period of the beginning of the year 2018 until the end of the year 2019. All the price data has been retrieved from the Yahoo Finance database except for Google trends indicator for the search term "cryptocurrency", which has been obtained from the Google trends database. The indicator shows the public interest and popularity of the search term in the whole world.

In this thesis, two different types of data used has been used. For correlation calculations, the author has used weekly price data. The reason behind that is the fact there is difference between observation size due to the fact that crypto assets are available for trade even during the weekends opposite to the other assets compared in this paper, which are traded mostly during the workdays as the stock exchanges are open. This shrinks the sample size to 104 weekly observations for the correlation calculations over the two years.

However, in the volatility analysis and calculations, the author has used daily price data in the same time period, because it interprets better results that are more accurate. Daily price data has been used as well in the day of the week effect analysis of the cryptocurrencies.

2.1.1 Descriptive statistics

Table 1 presents all the initial variables used in this paper. In this table the summary statistics presented is calculated from daily price data from the 1st of January of 2018 to 31st of December 2019, except for Google trends indicator for the search term "cryptocurrency" in the whole world (GTI World), which is calculated from weekly data in the same time period.

Table 1. Descriptive statistics

Variable	Mean	Median	S.D.	Min	Max
BTC	7483.80	7358.80	2548.50	3236.70	17527.00
XRP	0.48	0.36	0.37	0.19	2.90
ETH	332.00	215.00	260.00	88.40	1299.70
GTIWhole	13.20	9.00	14.70	5.00	95.00
S&P500	2829.95	2818.37	152.00	2351.10	3240.00
Crude oil	60.90	60.60	6.45	45.50	75.10
GOLD	1330.20	1311.10	97.00	1176.20	1550.30
VIX	15.80	14.70	3.90	9.70	31.50

Source: Author's calculation

All the variables in Table 1 have more illustrative look in the appendices 1-8, where there are daily graphs of the variables and additionally for the assets in these appendices there is 31-day volatility on the graphs.

2.2 Methodology

In this thesis, the author has used statistical analysis as the method of the research. I study the dynamics of the asset prices. In addition, I include a correlation analysis on the asset prices, which helps to understand different asset class prices and their behaviour towards other assets. There are two different correlation matrices, Table 2 has a correlation matrix between all the assets and volatility index available. Table 3 however provides the correlation matrix between the three crypto assets used in the empirical analysis and the Google trends indicator. In both correlations the weekly data has been used. Correlation analysis is done for the general understanding of the cryptocurrency price dynamics. In the statistical analysis part, the author will calculate volatility for the assets used in this thesis and analyse each asset volatility in comparison to the crypto assets. This is done by finding the daily returns of the assets and their variations and after that we have found the daily volatility and annualized volatility. In addition, the author has studied the day of the week effect of the crypto assets to find anomalies of the market and assets that investors could use. If there are persistent seasonal effect in the prices of crypto assets, this may suggest that there are persistent inefficiencies in the markets for crypto assets at least in the cases when crypto assets are converted to fiat currencies. For this the author has calculated the average daily returns for all of the exchange days of the cryptocurrencies. To interpret the results better this process has been done for the 2-year period and for suitable context each of the years separately have been also analysed. In this analysis part the daily price data of the assets have been used. Finally, there will be regression models estimated by using Ordinary Least Squares (OLS) method. With the OLS regressions the author is trying to explain the behaviour of the cryptocurrency prices and analyse certain co-movements with both related assets and public interest towards the cryptocurrencies. In the regression models the dependent variables used in the models are the crypto asset prices. As for explanatory variables the author has used all the variables in the Table 1. In the model, the author has used daily price data, which has been modified into weekly average price data except only for Google trends indicator, which was only available as a weekly indicator. Additionally, the author has used OLS method on the day of the week effect as well. This has been done by creating the dummy variables for all the weekdays except one. One dummy will be left out in order for the model to avoid autocorrelation issues. Throughout the thesis the author has used different Microsoft Office programmes and GRETL econometric software for the statistical analysis and regression models.

3. EMPIRICAL ANALYSIS & RESULTS

3.1 Correlation analysis

In order to understand the crypto asset price dynamics better, the author has taken it upon himself to calculate the correlations of the cryptocurrencies to other assets like S&P 500 index fund, crude oil, gold and to Volatility Index (VIX) as well, which is created by the Chicago Board Options Exchange (CBOE). Such analysis would enable the interpretation of cryptocurrency as a financial asset class. For the calculations, the author has used the three biggest crypto assets in terms of market capitalisation. Additionally, we look at the correlation of the search term "cryptocurrency" in Google Trends between the crypto asset prices.

Table 2. Asset price correlation matrix in 2018-2019 period

Variables	BTC	ETH	XRP	Crude oil	Gold price	S&P500	VIX
BTC	1	-	-	-	-	-	-
ETH	0.59	1	-	-	-	-	-
XRP	0.55	0.84	1	-	-	-	-
Crude oil	0.16	0.43	0.25	1	-	-	-
Gold	0.47	-0.14	-0.17	-0.41	1	-	-
S&P500	0.31	-0.29	-0.30	0.06	0.60	1	-
VIX	-0.24	-0.08	-0.07	-0.45	-0.07	-0.62	1

Source: Author's calculations

Table 2 represents the correlation matrix, where can be seen the correlation between all the asset classes and indicators used in the matrix. Most noteworthy would be to look at the Bitcoin's correlation between other asset classes. Bitcoin's correlation between Ethereum and Ripple is 0.59 and 0.55, respectively. This can be seen as a moderately positive correlation. However, the correlation between Ethereum and Ripple can be described as a strong positive linear correlation with the correlation coefficient between the assets as 0.84. This does not mean that Ethereum causes Ripple's price to move in the same direction or the other way around. Since Bitcoin has very significant market dominance in the cryptocurrency world, it is more likely that Bitcoin has a stronger effect on the price changes of Ripple and Ethereum thus their prices change more strongly in the same manner.

Table 2 represents us with the correlation information between the crypto assets and other asset classes. It can be seen from Table 2 that gold price and Bitcoin's price have a quite moderate positive correlation between these two assets. The correlation 0.47 can be interpreted as a significant measure. However, comparing these two commodities with Ethereum and Ripple, it is interesting to point out that gold has a negatively weak relationship with the correlation of -0.14 and -0.17, respectively. Both Gronwald (2019) and Jin *et. al* (2019) came to the same conclusion that Bitcoin can be referred to as a commodity, because of its high volatility. Crude oil, the other commodity in our correlation analysis, has a weak positive relationship with Bitcoin. The correlation of the crude oil price and Bitcoin price is 0.16.

Correlation calculations in Table 2 interpret that the correlation between Ethereum and crude oil is higher than it is with Bitcoin. Correlation, in this case, is 0.43, which can be explained as a moderate positive relationship between the assets. Additionally, crude oil and Ripple have much similar correlation relationship as Bitcoin does. The correlation coefficient for Ripple and crude oil is 0.25.

Correlation between cryptocurrencies and S&P500 index gives an interesting perspective. Bitcoin and S&P500 index have a correlation coefficient of 0.31 between the two assets, which is seen as a weak positive linear correlation. Opposite to Bitcoin, the other two crypto assets in this paper Ripple and Ethereum, have correlation coefficients of -0.3 and -0.29, respectively.

Volatility Index, which is an indicator of the S&P500 past prices and gives the S&P500 index fund's next 30-day volatility, has a negative correlation with the Bitcoin, Ethereum and Ripple. With Bitcoin, the correlation is -0.24. With Ethereum and Ripple coefficients are -0.08 and -0.07, which is close to 0. That means there is no meaningful relationship between Volatility Index and Ethereum and Ripple.

Table 3. Correlation matrix between crypto assets and Google Trends search term in 2018-2019

Variables	*GTIWhole*	*BTC*	*ETH*	*XRP*
GTIWhole	1	-	-	-
BTC	0.53	1	-	-
ETH	0.85	0.59	1	-
XRP	0.92	0.55	0.84	1

Source: Author’s calculations

Table 3 represents the correlation matrix between the Google Trends search term "cryptocurrency" and the crypto assets. Google Trends have their own statistical measure, which indicates the popularity and the number of searches for certain words or terms. The indicator is on the scale of 0-100. Data collected for this measure is from the 1st of January of 2018 to 31st of December of 2019. The measure represents all the google searches made for the search term "cryptocurrency" all over the world.

As the analysis results show from Table 3, then Ethereum and Ripple have strong positive linear correlation coefficients with the Google Trends search term "cryptocurrency". Correlation coefficients for these crypto assets are 0.85 and 0.92, respectively. Based on the correlation analysis it can be concluded that there is strong positive link between the attention and crypto assets. The same conclusion was made by the Urquhart (2018)'s paper.

3.2 Volatility

Crypto assets are considered very volatile assets. The author as taken it upon himself to calculate the historical volatility of the assets used in the analysis part of this thesis. For all the volatility calculations author has used daily closing prices of the assets. The volatilities for the assets have been calculated by finding the daily natural logarithms of returns. After that the daily variance has been found for all the assets. By doing this process it allowed to calculate the average daily returns, average daily variance, daily volatility and annualised volatility. For the annualised volatility the yearly trading days differ from 252 days and 365 days, because for crypto assets Bitcoin (BTC) and Ripple (XRP) there are 7 exchange days in a week and for other assets we have used 252 days for annualised volatility, because those assets can be traded 5 times a week.

Table 4. Volatility calculations in 2018-2019 period

Specification	BTC	ETH	XRP	GOLD	Crude Oil	S&P500
Average daily log returns	-0.09%	-0.34%	-0.35%	0.030%	0.002%	0.040%
Average daily variance	0.15%	0.34%	0.30%	0.005%	0.039%	0.009%
Daily volatility	3.90%	5.80%	5.45%	0.700%	1.990%	0.940%
Annualized volatility	75.20%	91.90%	104.20%	11.120%	31.540%	14.990%

Source: Author's calculations

From the Table 4 it can be seen that average daily returns for the crypto assets are all negative throughout the start of 2018 until the end of 2019 period. The average negative daily returns can be explained by the huge price drops after the 2017 year. For all the other assets that are used in this analysis those figures are positive. The same table describes daily variance of the assets compared. All three cryptocurrencies have high daily variance. For BTC it is 0.15%, for ETH it is 0.34% and XRP it is 0.3%. In comparison by looking at the daily variance by average for gold, crude oil and S&P500 these figures are lower. Daily volatility for the crypto assets is in the same region. Bitcoin, which is more established cryptocurrency, has a daily volatility coefficient 3.9%. The same figures for Ethereum and Ripple are 5.8% and 5.4% respectively. In comparison commodities gold and crude oil have daily volatilities of 0.7% and 1.99%. For the S&P500 index daily volatility is 0.9%. Annualized volatility over the 2-year period for BTC is 75.18%. For ETH and XRP it is 91.9% and 104.2% respectively. This indicates to us that there have been very high price movements over the course of these two years in the cryptocurrency market. Additionally, the daily volatility and annualised volatility is lower for the Bitcoin, which again shows the dominance of the asset in the market and that it way more established than Ethereum and Ripple. Annualized volatilities for the commodities gold and crude oil are 11.1% and 31.5% respectively. For S&P500 it is 14.9% during this period.

3.3 Day of the week effect

In this part of the analysis the author is trying to interpret if there are any anomalies of the crypto assets that investors can exploit. Caporale and Plastun (2019) studied exactly the same thing from the time period of 2013 until the end of 2017. In this part of the empirical analysis the author has used daily price data.

Table 5. Bitcoin's day of the week effect in 2018-2019 period

Average daily returns	Average annual returns	Day
-0.10%	-5.10%	Monday
-0.39%	-20.41%	Tuesday
-0.20%	-10.57%	Wednesday
-0.60%	-31.43%	Thursday
0.47%	24.51%	Friday
0.43%	22.21%	Saturday
-0.21%	-11.07%	Sunday

Source: Author's calculation

From the Table 5 it can be seen that based on the average daily returns, which interprets that on 5 days a week there are negative daily returns, which would suggest are good days for the buying. The best day for buying BTC would be Thursdays where the average daily returns are -0.6%. This analysis shows that for selling the best days would be Fridays and Saturdays, which have the daily returns on average 0.47% and 0.43% respectively.

Table 6. Bitcoin's day of the week effect in 2018

Average daily returns	Average annual returns	Day
-0.72%	-37.42%	Monday
-0.47%	-24.61%	Tuesday
-0.90%	-47.04%	Wednesday
-0.33%	-17.33%	Thursday
-0.07%	-3.43%	Friday
0.42%	22.06%	Saturday
-0.42%	-21.67%	Sunday

Source: Author's calculations

Table 6 provides the information based on the first year of the BTC returns. When throughout the 2018 and 2019 there were 2 trading days, which were good for selling then in 2018 there is only 1 and the best day for trading would be on the Saturdays, where the average daily returns on Saturdays in 2018 were 0.42% for Bitcoin. Best day for buying was on Wednesdays, which had the lowest average return in 2018 with -0.9%.

Table 7. Bitcoin's day of the week effect in 2019

Average daily returns	Average annual returns	Day
0.52%	27.21%	Monday
-0.31%	-16.29%	Tuesday
0.50%	25.91%	Wednesday
-0.88%	-45.53%	Thursday
1.01%	52.46%	Friday
0.43%	22.35%	Saturday
-0.01%	-0.47%	Sunday

Source: Author's calculations

From Table 7 there are more interesting anomalies to point out. Based on the calculations, in 2019 there were 4 days in a week which were great for selling Bitcoin. These days were Monday, Wednesday, Friday and Saturday. Out of all these days Friday was the best for selling, because of the average daily return, which was 1.01%. Best day for buying Bitcoin was on Thursdays when the average daily return was -0.88%.

Table 8. Ripple’s day of the week effect in 2018-2019 period

Average daily returns	Average annual returns	Day
-0.76%	-39.45%	Monday
-0.65%	-33.74%	Tuesday
-0.37%	-19.32%	Wednesday
-0.83%	-43.26%	Thursday
0.23%	11.83%	Friday
0.16%	8.52%	Saturday
-0.19%	-10.13%	Sunday

Source: Author’s calculations

For Ripple (XRP) there are similarities over the 2-year period as for Bitcoin. Based on the calculations in Table 8 it can be seen that best days for buying the XRP are Mondays and Thursdays, which have the average daily returns of -0.76 and -0.83 respectively. Tuesday is as well good day for buying XRP with the average daily return coefficient of -0.65%. Table 8 suggests that it would be smart to buy during the beginning of the week and sell in the end of the week. Best days for the selling are Fridays and Saturdays with the coefficients of 0.23% and 0.16% respectively.

Table 9. Ripple’s day of the week effect in 2018

Average daily returns	Average annual returns	Day
-1.75%	-90.86%	Monday
-1.17%	-60.84%	Tuesday
-0.96%	-49.73%	Wednesday
0.10%	5.00%	Thursday
0.20%	10.28%	Friday
-0.01%	-0.69%	Saturday
-0.09%	-4.55%	Sunday

Source: Author’s calculations

Table 9 presents the first half of the observation period results to us. In 2018 the beginning of the week was especially good for buying XRP. For selling the best days were Thursdays and Fridays with the coefficients of 0.1% and 0.2% respectively. The best day for buying was Mondays when the average daily returns during 2018 was -1.75%. Tuesday offered also negative daily returns on average.

Table 10. Ripple's day of the week effect in 2019

Average daily returns	Average annual returns	Day
0.23%	11.97%	Monday
-0.14%	-7.16%	Tuesday
0.21%	11.09%	Wednesday
-1.76%	-91.52%	Thursday
0.26%	13.38%	Friday
0.34%	17.74%	Saturday
-0.30%	-15.70%	Sunday

Source: Author's calculations

The second half of observations provide the results which are described in the Table 10. It can be seen that in 2019 there were 3 days that were good for buying the XRP. Especially great day for buying was the Thursdays, because average daily returns throughout 2019 was -1.76%. Best days for selling the XRP were during the Fridays and Saturdays. During these days the average daily return coefficients were 0.26% and 0.34%.

Table 11. ETH day of the week effect in 2018-2019 period

Average daily returns	Average annual returns	Day
-0.18%	-9.46%	Monday
-0.52%	-27.23%	Tuesday
-0.59%	-30.75%	Wednesday
-0.84%	-43.59%	Thursday
0.42%	22.02%	Friday

Source: Author's calculations

Table 11 represents the day of the week effect of the Ethereum (ETH). As Ethereum can be exchanged only 5 times a week which is why the analysis has been done on the 5 days. Table 11 provides the information that especially good days for buying ETH is from Tuesday to Thursday. On Tuesdays the average daily return was -0.52%, on Wednesday it was -0.59% and on Thursdays it was -0.84%. Best day during the 2-year period for selling the ETH was on Fridays with the coefficient of 0.4%.

Table 12. ETH day of the week effect in 2018

Average daily returns	Average annual returns	Day
-0.96%	-49.75%	Monday
-0.63%	-32.91%	Tuesday
-1.65%	-85.60%	Wednesday
-0.27%	-13.88%	Thursday
0.12%	6.48%	Friday

Source: Author's calculations

The first part of the observations provide the similar day effect results. Table 12 shows that Mondays and Wednesdays are best days for buying the ETH with the mean daily return coefficient of -0.96% and -1.65% respectively. The best day for selling remains the same as it was for the whole 2-year period, which is Friday with the coefficient of 0.1%.

Table 13. ETH day of the week effect in 2019

Average daily returns	Average annual returns	Day
0.59%	30.83%	Monday
-0.42%	-21.65%	Tuesday
0.46%	24.11%	Wednesday
-1.41%	-73.29%	Thursday
0.72%	37.56%	Friday

Source: Author's calculations

Table 13 presents the second half of the observations. In 2019 there were 3 days which were good for selling ETH. Monday had the mean daily return of 0,59%. Wednesday and Friday had the same coefficients of 0,46% and 0,7%. For buying the best days of the week were Tuesdays and Thursdays. Thursdays were especially good days in 2019 for buying ETH with mean daily return coefficient of -1,4%.

3.4 Regression analysis

The author regresses and analyses the effects of the other assets on the cryptocurrencies, which in the regression models are independent variables. Through the regression analysis author interprets the price movement effects on the dependant variables and tries to find related trends that investors may use as potential predictors for crypto assets. In the regression analysis the author has used daily price data of the assets which has been modified into the weekly average price data, because one of the independent variables is Google Trends indicator (GTIWhole) for the attention of the search term "cryptocurrency", which was only available as a weekly indicator. The indicator shows the search term's population around the whole world. Additional regression models have been conducted on the day of the week effect. In those regression models the author has used daily price data. The author has conducted the models on the whole 2-year time period and has additionally ran the models separately on each year. Only the important and significant models are reported in the paper.

Table 14. Regression model for dependent variable ld_BTC in 2018-2019 period

	Model 1		
Variable	**Coef.**	**St. Error**	
const	0.002	0.008	
ld_S&P500_1	2.009	0.818	**
ld_GTIWhole_1	0.109	0.057	*
ld_GTIWhole_2	0.151	0.055	***
ld_GTIWhole_3	0.172	0.054	***
ld_VIX	0.146	0.054	***
ld_VIX_1	0.253	0.093	***
N	**104**		
Adjusted R-squared	**0.185**		
Durbin-Watson	**1.541**		

Source: Author's calculations

Table 14 describes us the Model 1 of regression. In this model the dependant variable is the ld_BTC, which is the logarithmic difference of BTC prices. Logarithmic difference has been taken from all the independent variables as well. In Model 1 the author has put together a model, which shows mainly significant variables. As can be seen from the Model 1 the lag of S&P500_1 price seems to have a positive significant effect on the BTC price at the 5% level. This means that if the last week's return of the S&P500 is higher by 1% then it is estimated that this week's return of the BTC is higher by 2%. The cumulative impact of lagged Google trends indicator reveals strong impact on search interest and price increases. For Google trends indicators (GTIWhole), it can be pointed out that the lag of the GTIWhole has positive significant effect on the return of the BTC price at the 10% level. This means that if the last week's GTIWhole increases by 1% then it can be estimated that this week's BTC return will increase by 0,11%. For the same indicator, but the second lag there is a positive significant effect on the return of the BTC price at the 1% level.

When the second lag of GTIWhole increases by 1% then it is expected that BTC price increases by 0.15%. The third lag of the GTIWhole is significant at 1% level as well and has positive effect on the BTC price. When the third lag of GTIWhole increases by 1% then it is estimated that BTC price has positive return of 0.17%. Both VIX and its lag have positive significant effect on the price of the BTC price at 1% level. The effect of VIX and it lag affect the BTC price with 0.14% and 0.25% respectively. Other variables like gold and crude oil did not have any significant effect on the BTC price. For this model the adjusted R-squared is 0.18% and the Durbin-Watson coefficient was 1.5. This model shows there is slight autocorrelation between the variables and this may be slight weakness in the model and its predictors.

Table 15. Regression model for dependent variable ld_ETH in 2018-2019 period

	Model 2		
Variable	**Coef.**	**St. Error**	
const	−0.003	0.011	
ld_Crudeoilprice	0.553	0.326	*
ld_SP500Price	−2.316	0.640	***
ld_GTIWhole_1	0.133	0.078	*
ld_GTIWhole_2	0.109	0.073	
ld_GTIWhole_3	0.257	0.072	***
N	**104**		
Adjusted R-squared	**0.178**		
Durbin-Watson	**1.661**		

Source: Author's calculations

Table 15 shows the regression Model 2 where the dependent variable is price of Ethereum. In Model 2 there can be seen slight differences with the Model 1. Crude oil price has significant positive effect on the ETH price at the 10% level. It means that if the crude oil's price increases by 1% then ETH price increases 0.55%. S&P500 has a negative significant effect on the price of the ETH at 1% level. This means that if the S&P500 price increases by 1% then the ETH price drops by 2.3%. For Google trends indicators only the lag and the third lag have positive significant effect on the ETH price at 10% and 1% level respectively. The effect of the lag on the ETH price is 0,13% and the third lag 0.25%. All the other independent variables were not significant and were not added in the model. The adjusted R-squared for Model 2 is 0.17% and the Durbin-Watson coefficient for the same model is 1.66. Once again it shows there is slight autocorrelation between the variables, which indicates the weakness in the model.

Table 16. Regression model for dependent variable ld_XRP in 2018-2019 period

	Model 3		
Variable	**Coef.**	**St. Error**	
const	−0.006	0.011	
ld_GTIWhole_2	0.153	0.071	**
ld_GTIWhole_3	0.213	0.071	***
ld_SP500Price	−1.544	0.624	**
N	**104**		
Adjusted R-squared	**0.118**		
Durbin-Watson	**1.647**		

Source: Author's calculations

Table 16 provides the third regression model where the dependent variable is Ripple price (XRP). In Model 3 there can be seen that only 3 independent variables have significant effect on the XRP price. The second lag of GTIWhole has a positive significant effect on the price of the XRP at the 5% level. When the second lag of the GTIWhole increases by 1% then it is expected that this week's return of the XRP increases by 0.15%. The third lag of the GTIWhole has positive significant effect as well at 1% level. When the third lag of GTIWhole increases by 1% then it is estimated that XRP price increases by 0.21%. S&P500 has negative significant effect on the price at 5% level. When the S&P500 increases by 1% then it is estimated that XRP price drops by 1.54%. The adjusted R-squared for Model 3 is 0.11% and the Durbin-Watson coefficient is 1.65. All three models have slight autocorrelations.

While analysing the day of the week effect through the OLS regression method the author created models for 3 different time periods. The whole 2-year time period and each year separately were under the observation scope. From all the models created the most significant results appeared in the year 2019. The whole 2-year time period did not interpret any significant results for Bitcoin, Ethereum or Ripple. When each year separately was analysed then only 2019 year produced significant results for all the crypto assets used in the analysis part that are worth reporting. However, 2018 year did not bring out any significant results worth reporting. Table 17 shows the regression model for dependent variable ld_BTC in the year 2019. In this model the author has taken logarithmic differences of the BTC price for the dependent variable. In Model 4 the author has left out Thursday's dummy variable.

Table 17. Regression model for dependent variable ld_BTC in 2019

Variables	Model 4 Coef.	St. Error	
const	−0.008	0.004	*
D_Mon	0.013	0.006	**
D_Tue	0.005	0.006	
D_Wed	0.013	0.006	**
D_Fri	0.018	0.006	***
D_Sat	0.013	0.006	*
D_Sun	0.008	0.006	
N	**365**		
Adjusted R-Squared	**0.010**		
Durbin-Watson	**2.034**		

Source: Author's calculations

Table 17 shows that only in 4 days there are positive significant results. Based on our initial day of the week calculations that were done in Excel the results are similar. It can be seen that Monday, Wednesday, Friday and Saturday are positively significant, which means that on those days BTC price increases. On Fridays there seems to be the highest increases in price at the 1% level of significance. On Mondays, Wednesdays and Saturdays the increase of the return is 0.013%. Mondays and Wednesdays are significant at 5% level and Fridays at 10% level. Adjusted R-squared for this model is indeed minor (0.01) but statistically significant coefficients at certain weekdays may serve as a weak evidence of lasting inefficiencies in the market. Durbin-Watson coefficient for the model is approximately 2, which shows there is no autocorrelation issues in the model.

Table 18. Regression model for dependent variable ld_XRP in 2019

Variables	Model 5 Coef.	St. Error	
const	−0.017	0.005	***
D_Mon	0.019	0.007	***
D_Tue	0.016	0.007	**
D_Wed	0.019	0.007	***
D_Fri	0.020	0.007	***
D_Sat	0.021	0.007	***
D_Sun	0.014	0.007	**
N	**365**		
Adjusted R-Squared	**0.018**		
Durbin-Watson	**2.035**		

Source: Author's calculations

Table 18 provides the day of the week effect in a regression model. In Model 5 the author has left out Thursday's dummy variable. Based on our day of the week calculations in Excel for Ripple in 2019 it was concluded that best days for selling XRP were Mondays, Wednesday, Fridays and Saturdays in 2019. However, our regression model shows positive significant results on all weekdays used in this regression. In Model 5 it can be seen that Monday, Wednesday, Friday and Saturday dummies are all significant at 1% level. Additionally, on those days the returns of the XRP were the highest. The same result appeared from our initial calculations. Adjusted R-squared for Model 5 was approximately 0.02 and the Durbin-Watson coefficient 2.04, which shows negative autocorrelation in the model.

Table 19. Regression model for dependent variable ld_XRP in 2019

	Model 6		
Variables	**Coef.**	**St. Error**	
const	−0.014	0.006	**
D_Mon	0.020	0.009	**
D_Tue	0.009	0.009	
D_Wed	0.018	0.009	**
D_Fri	0.021	0.009	**
N	**261**		
Adjusted R-Squared	**0.014**		
Durbin-Watson	**1.820**		

Source: Author's calculations

Table 19 represents the day of the week regression model. In Model 6 the author has left out the Thursday's dummy variable. From Table 19 it can be seen that Monday, Wednesday and Friday are all positively significant at 5% level. From our initial day of the week calculations for XRP it was concluded that the best days for selling the XRP were Mondays, Wednesdays and Fridays in 2019. Based on the results in Model 6 it can be confirmed that our initial calculations provided the same conclusion for the XRP in 2019.

3.5 Discussion of the results

Throughout this Bachelor Thesis paper the author was examining the price dynamics of the crypto assets. The author conducted several analysis in order to answer to the research questions. The empirical analysis started off with the correlation matrices. Based on the results of the correlation

analysis it can concluded that all three crypto assets were in positive correlation with crude oil during 2018-2019 period. Strongest correlation was between Ethereum and crude oil. Bitcoin, however, was the only crypto asset that had positive price correlation with gold and S&P500 index. Other crypto assets had negative correlations with these assets. All three crypto assets were in strong positive correlation with each other, which can be due to the fact that Bitcoin has very large market dominance of 67% and with the price changes it affects other cryptocurrencies as well.
The other correlation matrix that was conducted in this paper looked at the link between the Google Trends search term “cryptocurrency” and BTC, XRP and ETH price correlation. As in the paper written by Urquhart (2018), there was positive relationship between Google Trends indicator, which shows the attention of the trend, and Bitcoin volatility. In the correlation analysis in this paper, it can be concluded that Google Trends indicator during 2018-2019 period had positive correlations with the crypto assets. For ETH and XRP the correlation was 0.9 and 0.8 respectively. For Bitcoin the correlation was lower with the coefficient of 0.5. Our correlation analysis suggests that there is link between the price changes and attention of the crypto assets. This may also refer to dual causality: first the public interest may drive the price dynamics, but also the significant surge in prices may have an impact on search activity.
Second, the volatility analysis was conducted. Based on the volatility calculations the author noticed remarkable differences of volatilities in comparison of other assets, which indicates that the crypto assets are indeed very speculative and risky. Based on the volatility analysis in this paper, parallels can be drawn with Baek & Elbeck’s (2015) paper. Authors findings suggested that BTC’s daily volatility was 26 times higher than S&P500 index. This paper’s findings suggest something similar. Based on the calculations it can be concluded that crypto assets have extremely high volatility compared to other asset classes. Our volatility calculations suggest that crypto assets are used for speculative assets, because of their high volatility, which is why cryptocurrencies are traded more in short-term than long-term. Based on our volatility calculations, it can be concluded that crypto assets are not safe haven assets and should not be used for hedging the risk. As Grobys *et. al* (2020) concluded that short-term trading provides higher returns in crypto assets. This can also be the reason for the high volatility among the crypto assets.
Thirdly, this paper offered the overview of the day of the week effect among the cryptocurrencies. If there are persistent seasonal effects on the prices, this may imply that market may still be somewhat inefficient. Based on our regression results, the author found anomalies while looking at the year 2019. There were no significant results for the whole 2-year period or only 2018 year. According to the Caporale and Plastun (2019) paper only BTC had anomalies on Mondays during 2013-2017 period. During this period Mondays offered abnormal returns for the investors. Our

findings suggested otherwise. Based on our regression models all of the 3 crypto assets analysed had anomalies, but only in 2019. These seasonal patterns imply that cryptocurrency market is still inefficient, which suggests investors entering in the market do not have full extent of the knowledge. This is understandable considering the price movements and the length of market's existence. When looking at the whole 2-year period no anomalies were found. Same was concluded when the author looked at the 2018 year separately.

Finally, in the empirical analysis part, the author conducted regression models for better understanding of the crypto asset prices. Regression Models 1-3 all had significant relationship with Google Trends indicator. For BTC all of the Google Trend indicator's lags were significant and showed positive explanation on the price of BTC. For ETH only the first lag and third lag had the same impact on the price. And for the XRP the second and third lag explained the price of the XRP positively. Based on these models, it can be concluded that the social media attention has impact on the crypto asset prices. However, based on our models, our research has been conducted on the time period of 2018-2019 and our model have slight positive autocorrelation, which can be viewed as the weakness in our regression.

CONCLUSION

By seeing the incredible returns on the crypto assets and the growing media attention of this financial instrument increased my interest of understanding these assets. The high volatility of the cryptocurrencies and lack of knowledge were the key reasons for this paper. The aim of this paper was to understand and explain the price dynamics of the crypto assets through the statistical analysis.

Based on the empirical analysis in this paper, crypto asset prices do have trends, which affect the prices of the cryptocurrencies. Crypto assets are mainly used for the short-term trading, which explains why there is very high volatility among the assets. Regression results in this paper showed that attention of the cryptocurrencies have positive link between the price increase of the assets. With their high volatility and short-term trading crypto assets are speculative financial instruments, because of their high risk and high return. Investors in crypto market are definitely very active traders for high returns. Based on the correlation analysis then cryptocurrencies tend to be similar to the crude oil, which is a commodity that is very volatile. The volatility is the reason why crypto assets can not be used as safe haven assets like the commodity gold. The results regarding the anomalies, showed that only in 2019 crypto assets had especially high returns during Fridays and Saturdays, which were the best days for selling of the assets.

There is no clear legal or financial definition for crypto assets. Opposite to commodities or financial assets, the intrinsic value is zero. Despite relatively large turnover, there are persistent seasonal patterns, which may imply that the market has remained rather inefficient over the years. Positive impact on the search activity of the prices may imply that most of the price dynamics is still influenced by the inflow of investors who may have rather limited knowledge on the crypto assets. In addition, the large price shifts of fundamentals are triggering the additional interest towards crypto assets. This implies that the prices remain rather vulnerable to potential negative news or signals, which may trigger both buying and selling pressure.

This study has potential limitations. Models used for explanation of the price have been conducted on the weekly prices and there is slight positive autocorrelation. As for the attention of crypto assets it would be better to have daily indicator, which would interpret the better results. Additionally, the 2-year observation period is too small for interpretation of the study. This can be mitigated as the time goes by and the sample increases or by applying panel data approach to the selection of crypto assets. For regulators and investors, this little exercise may serve as an evidence that the market of crypto assets has remained very risky and speculative.

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APPENDICES

Appendix 1. Bitcoin's chart

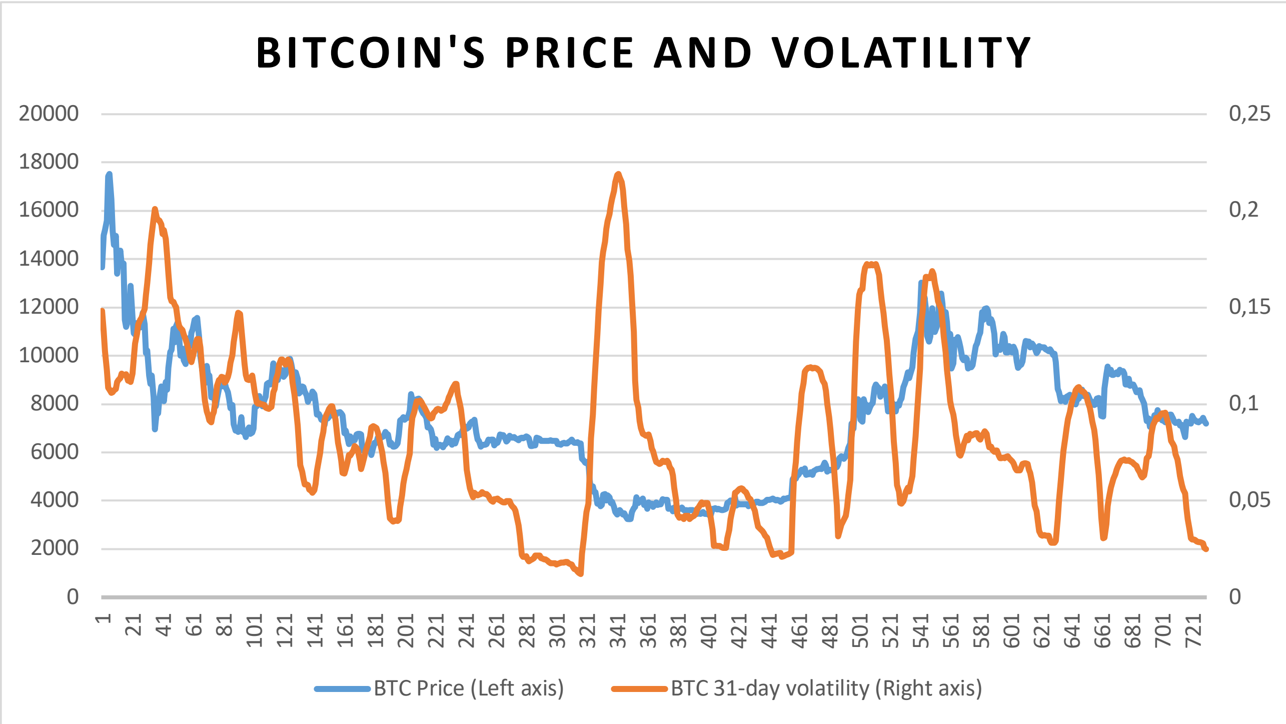

Figure 2. Descriptive chart of Bitcoin
Source: Yahoo Finance, author's calculations

Appendix 2. Ethereum's chart

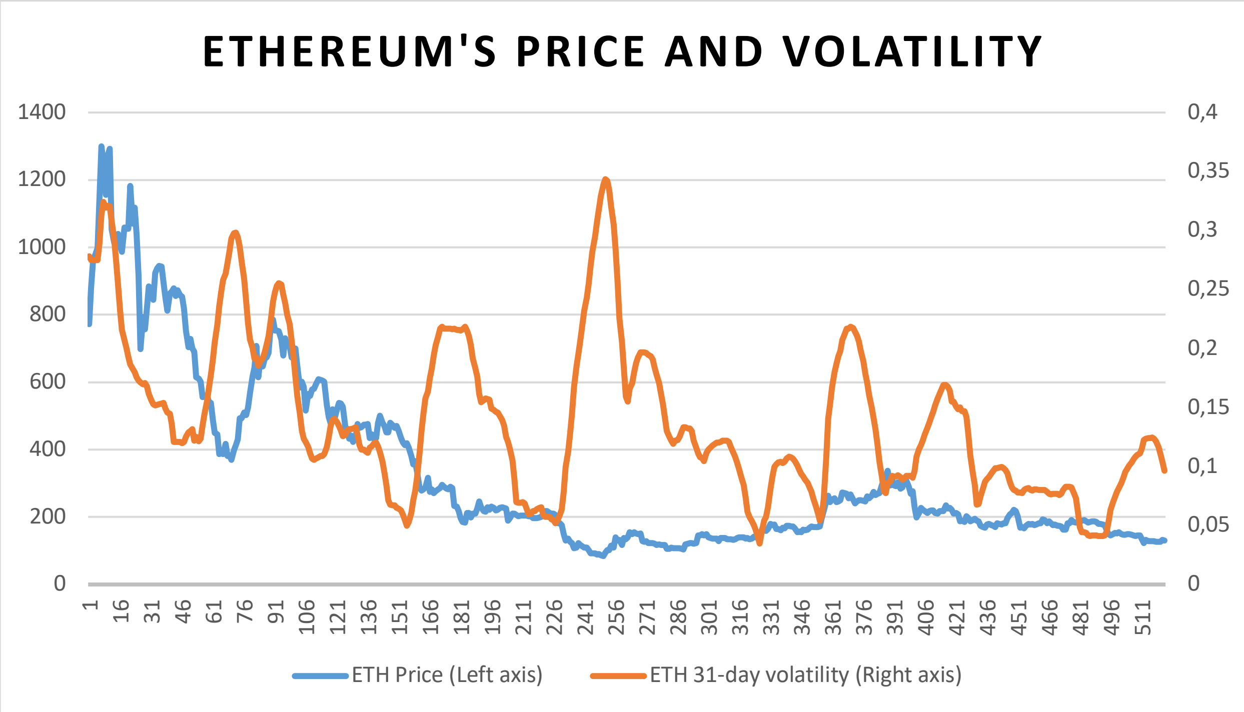

Figure 3. Descriptive chart of Ethereum
Source: Yahoo Finance, author's calculations

Appendix 3. Ripple's chart

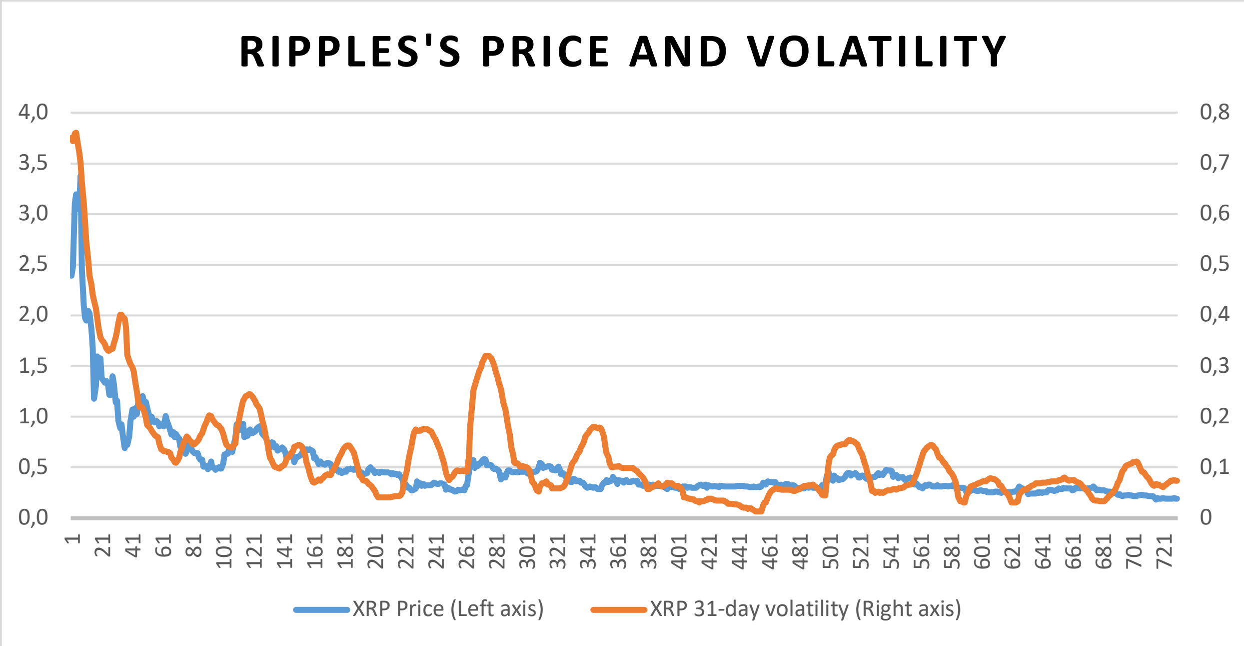

Figure 4. Descriptive chart of Ripple
Source: Yahoo Finance, author's calculations

Appendix 4. S&P500 chart

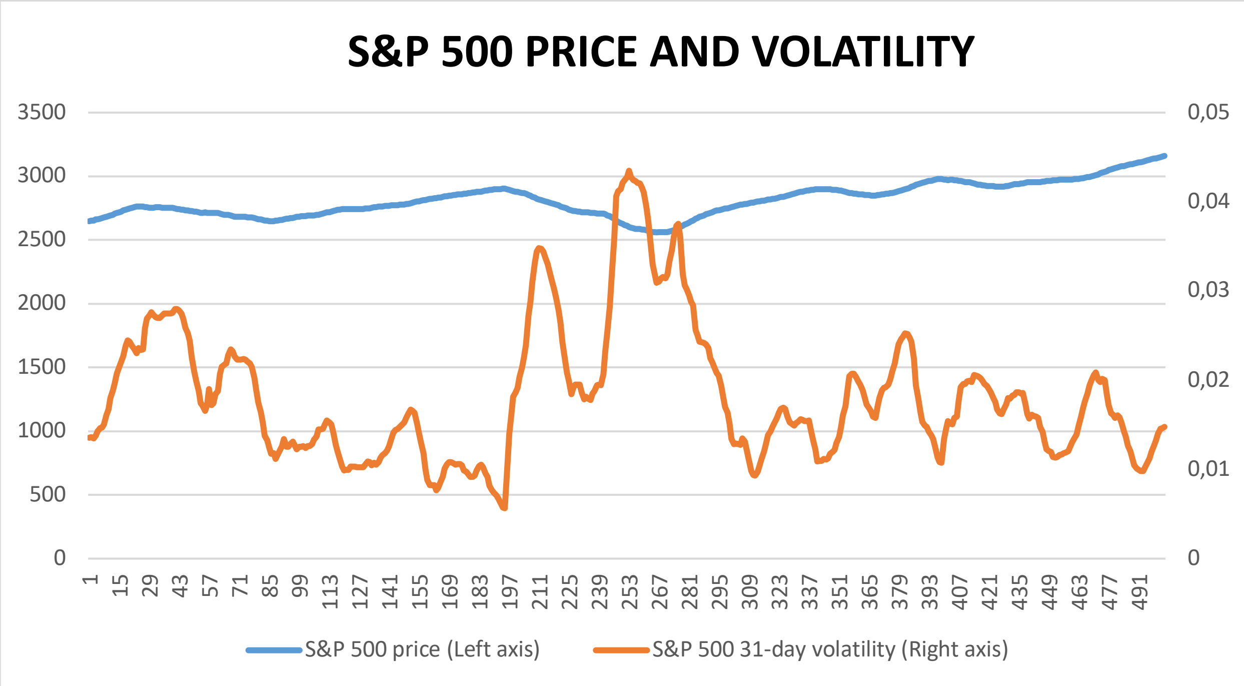

Figure 5. Descriptive chart of S&P 500
Source: Yahoo Finance, author’s calculations

Appendix 5. Crude oil's chart

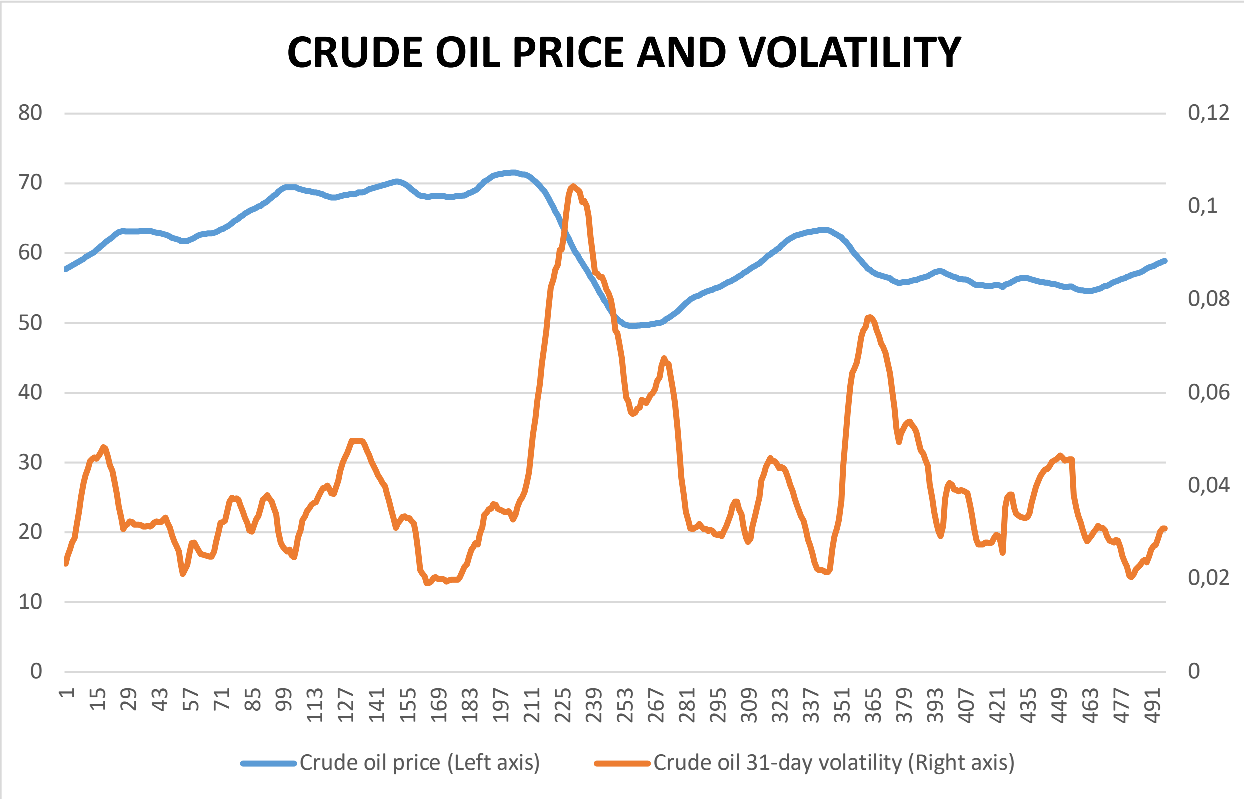

Figure 6. Descriptive chart of crude oil
Source: Yahoo finance, author's calculations

Appendix 6. Gold chart

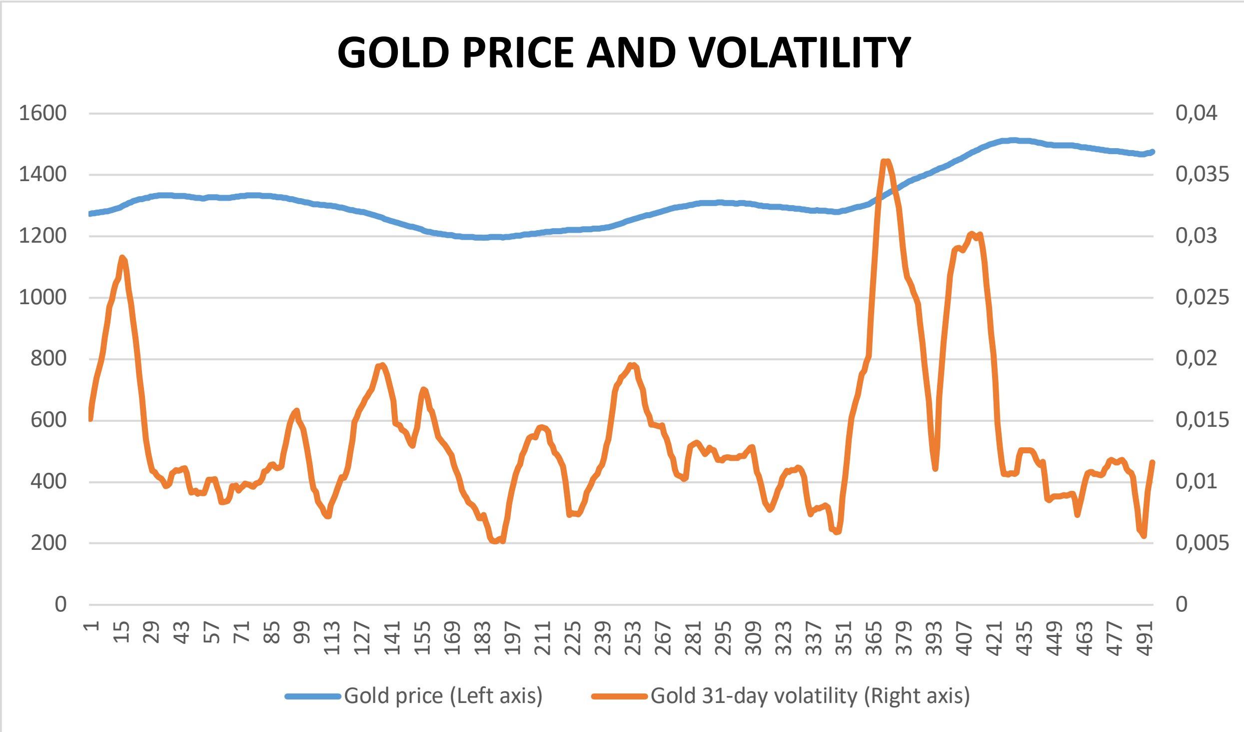

Figure 7. Descriptive chart of gold
Source: Yahoo Finance, author's calculations

Appendix 7. Chart of VIX

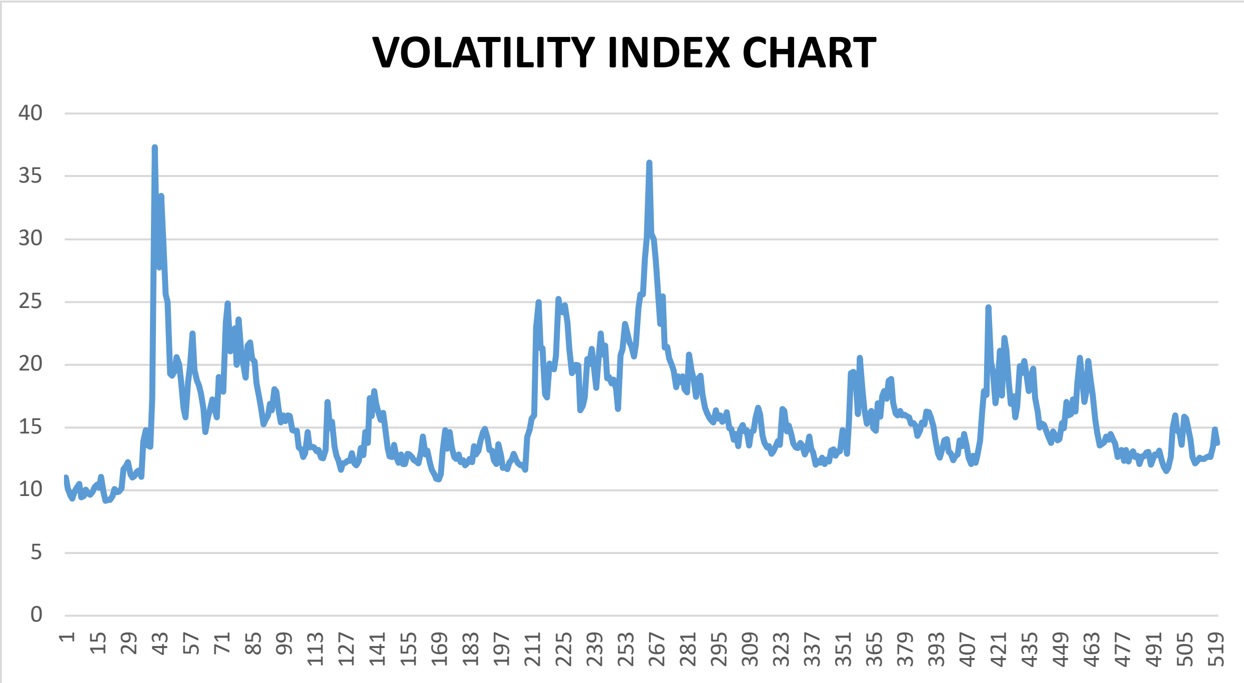

Figure 8. Descriptive chart of VIX
Source: Yahoo Finance, author's calculation

Appendix 8. Google trends chart

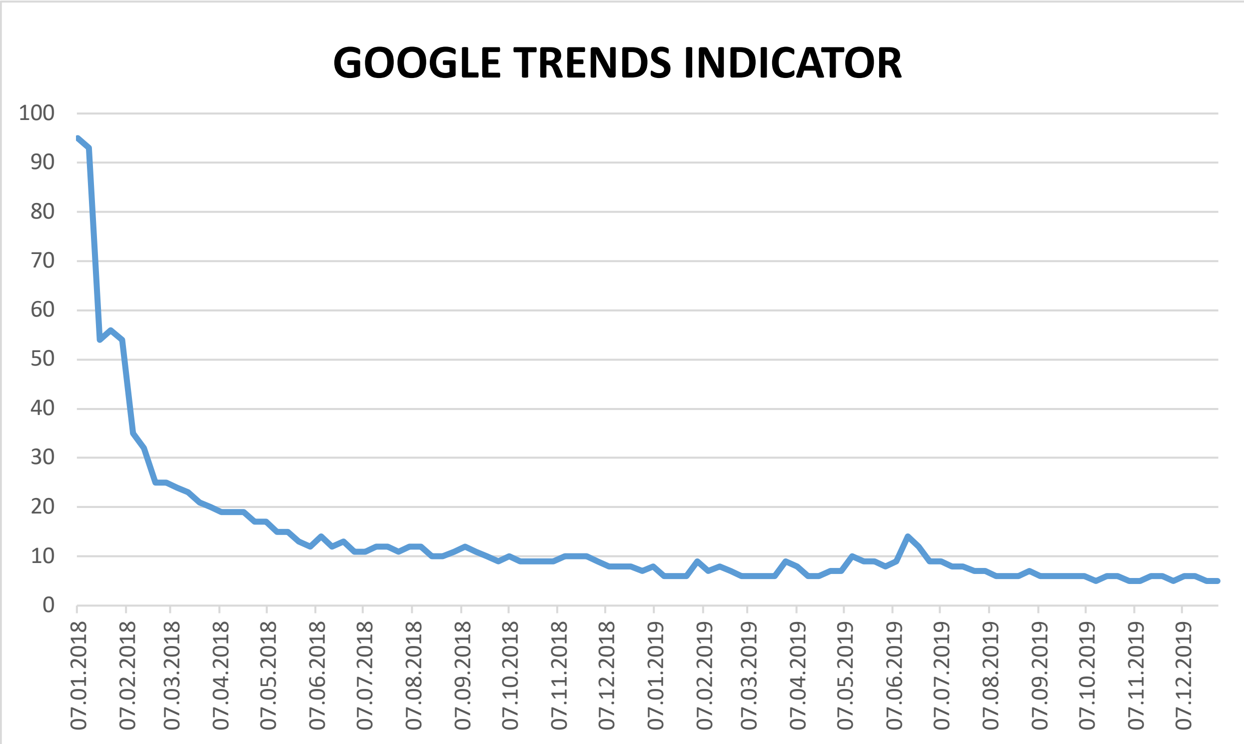

Figure 9. Descriptive chart of Google trends indicator
Source: Google Trends, author’s calculation

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