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What drives the price development of cryptocurrencies?

An empirical study of the cryptocurrency market

Bachelor Thesis (15 hp) at the Centre for Finance

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Abstract

The novelty, the rapid growth rate and the high volatility of cryptocurrencies have led to great uncertainty without any consensus on whether cryptocurrency is a medium of exchange or a speculative investment. This uncertainty raises the question of what actually drives the price development of cryptocurrencies. Furthermore, the great volatility questions if the risk-adjusted return of cryptocurrencies have been higher than the market return. In this paper, the first question is answered by analysing three categories of variables: macro-financials, supply-demand and attention, and their effects on the cryptocurrency market. The findings imply that size of the cryptocurrency market, trading volume, news articles and views on Wikipedia all have significant effects on the price development, while macro-economic factors do not. The second question is analysed through the M^2-measure, suggesting that investors have been well-compensated for the risk when investing in cryptocurrencies.

Keywords: Cryptocurrency, Cryptocurrencies, Bitcoin, Ethereum, Ripple, Litecoin, Panel Data, Risk-adjusted Return

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1. Introduction

The concept of cryptocurrencies was introduced to the market in the mid 2000s as a non-compliance action against the highly centralized banking and monetary system. This launch came partly as a response to the Global Financial Crisis of 2008, with the great mistrust of the United States' government and financial institutions also leading up to this revolution (Bariviera, Basgall, Hasperué and Naiouf, 2017). Today, over one thousand cryptocurrencies exist in various forms (CoinMarketCap, 2018), challenging the fundamentals of the monetary system with fiat currencies[1] by providing a payment system completely independent from governmental bodies and clearing houses. Cryptocurrencies are based on the blockchain technology[2] that allows for electronic transactions dependent on cryptography rather than trust in a verifying third party (Nakamoto, 2008).

Since cryptocurrencies do not rely on an interest rate, nor do they provide this feature, valuation models based on interest rates are meaningless (Glaser, Zimmarmann, Haferhorn, Weber and Siering, 2014). The price is thus dependent on how users value the cryptocurrencies based on any available information from news or web sources (Glaser et al., 2014). With this in mind, cryptocurrency price could be partly based on a supply and demand valuation, and since the number of coins is limited, an increase in demand would therefore be followed by an increase in price, everything else equal. Whether cryptocurrencies such as Bitcoin, Ripple, Ethereum and Litecoin are to be defined as currencies or speculative investments remains an ongoing discussion. According to Glaser et al. (2014) most new Bitcoin users treat it as an investment rather than a currency. The question regarding how to classify Bitcoin has been further investigated by Dyhrberg (2016), who analysed to what extent the price of Bitcoin correlated with gold price and USD.

In many ways, the ambition to classify cryptocurrencies is an attempt to understand the new asset, and by extension understand the behavior of its price. Can we, despite the great price volatility, see a future where cryptocurrencies have replaced traditional money, or will they serve mainly as speculative investments? Do the users get enough compensation for the risk they take on when buying cryptocurrencies? And what is it that, in the end, drives the price development of these new assets?

[1] Traditional money, further described in section 2.2.2
[2] Technology allowing for cryptographic verifications, further described in section 2.2.1

The remainder of the thesis is structured as follows. Section 2 continues with the introduction and clarifies some background facts about the topics involved and moreover states the problem and research questions, followed by the theory and literature study. In section 3, the dependent and independent variables are introduced together with some descriptive statistics. In section 4, method, tests, and transformations are stated. In section 5, the obtained results are presented and discussed, alongside a sub-section of robustness analysis. Finally, the conclusion is stated in section 6.

2. Background

2.1 Cryptocurrencies

According to the European Central Bank (ECB, 2012), the taxonomy of virtual currencies is divided into three main types. The first is (1) *Closed virtual currency schemes*, and an example of this is World of Warcraft (WoW) Gold, which can be bought, sold, earned and used only within the virtual world. The second type is (2) *Virtual currency schemes with unidirectional flow*, where the virtual money can be used within a virtual world (e.g. coins in Candy Crush Saga by King) but is bought with traditional money. However, it cannot be converted back into fiat currency. The virtual currency that will be the focal point for this thesis is type (3) *Virtual currency schemes with bidirectional flow*. Users of this type can convert their money in either way at the current exchange rate of that currency and use the money to buy goods and services in both the virtual and real world (ECB, 2012).

A subtype to *virtual currency schemes with bidirectional flow* is cryptocurrency, intended as a medium of exchange in a digital context. The foundation of cryptocurrencies is the blockchain technology, which uses a decentralized ledger as the verification instrument. Because it is verified and logged with cryptography rather than relying on a third party, cryptocurrencies are considered trustworthy (Cointelegraph, 2017). Bitcoin, Ethereum, Ripple and Litecoin are all examples of cryptocurrencies, and will be briefly introduced below.

2.1.1 Bitcoin (BTC)

Bitcoin is today the largest cryptocurrency with a market capitalization of $134 940 million (2018-03-27) (CoinMarketCap, 2018). Bitcoin was launched in 2009 by a group, or a single person, under the pseudonym Satoshi Nakamoto but the origin is still not completely known (Bitcoin, 2018). Bitcoin is based on the blockchain technology, which is the cornerstone of the decentralized currency system. Up until 2013, when active trading of Bitcoin took off, Bitcoin had mostly been associated with illegal activities, such as the purchasing of sex and drugs (Blau, 2018). However, in recent years when cryptocurrencies have become more acknowledged by the common people, Bitcoin is also used in a legal context. The number of Bitcoins is capped at 21 million coins, and with the prespecified pace of mining, this number will be reached in year 2140 (Bariviera et al., 2017).

2.1.2 Ethereum (ETH)

The digital platform Ethereum was introduced in 2014 by the Swiss, non-profit organization Ethereum Foundation (Ethereum Project, 2018) and is the second largest cryptocurrency with a market capitalization of $46 009 million (2018-03-27) (CoinMarketCap, 2018). Similar to Bitcoin, Ethereum is based on the open source blockchain technology. The difference from Bitcoin is that Ether, the currency, is only valid on the platform Ethereum (Ethereum Project, 2018), whereas Bitcoin can be used wherever in the world it is accepted, in the same way as fiat currencies. On the Ethereum Platform, individuals can issue their own tradable assets and tokens, apply for crowdfunding for an Ethereum-based project and create organizations that exist on the blockchain (Ethereum Project, 2018). The operating and managing of the platform is done by the Ethereum Foundation, and is dependent on donations, in either Bitcoin or Ether (Ethereum Project, 2018). In this thesis, both the currency and the platform are referred to as Ethereum.

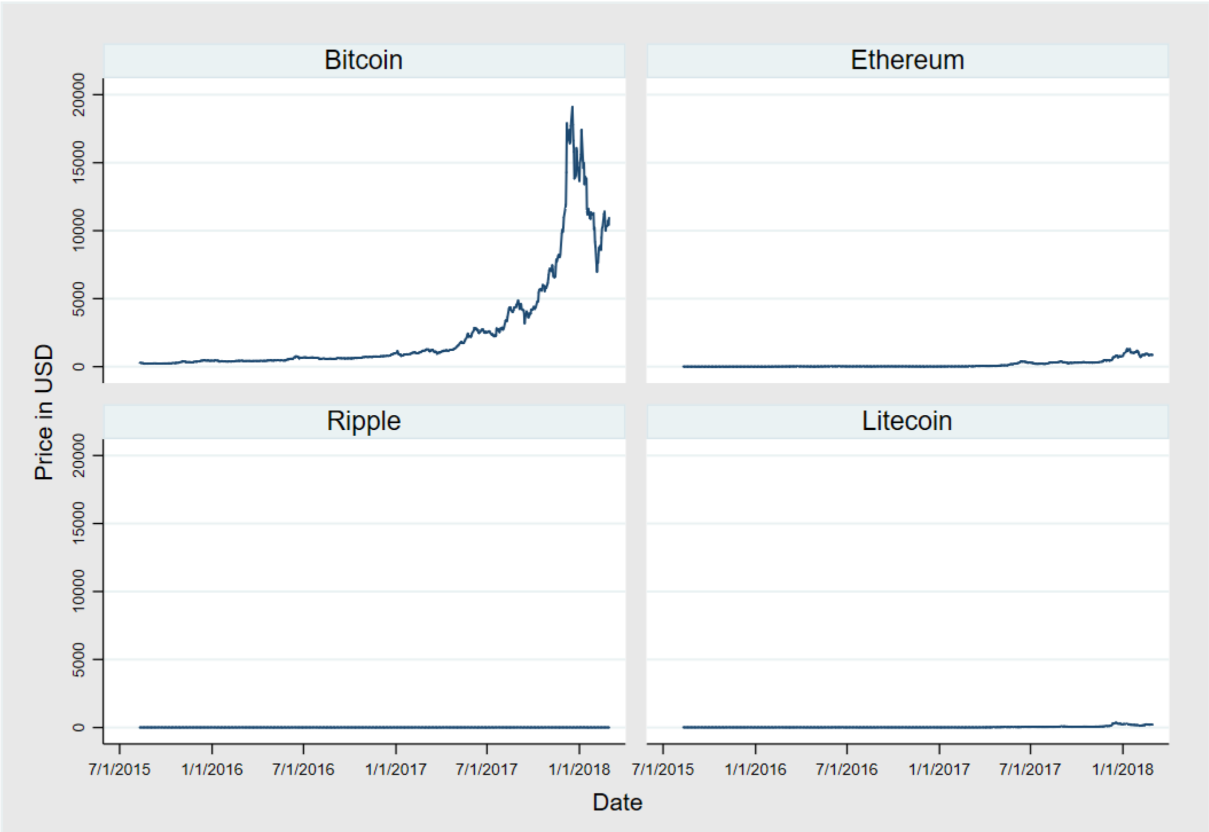
2.1.3 Ripple (XRP)

Ripple was introduced in 2012 (Ripple, 2018) and is the third largest cryptocurrency with a market capitalization of $22 693 million (2018-03-27) (CoinMarketCap, 2018). The Ripple network is a real time payment system built on a peer-to-peer, open source technology. This payment system can be used by both banks and individuals, and enables for quick, international transactions without the involvement of intermediaries (Ripple, 2018). The system can handle up to 1500 transactions per second, in comparison to Bitcoin which can handle 3-6 transactions per second. Both fiat currencies and Ripple can be transferred through the Ripple network (Ripple, 2018).

2.1.4 Litecoin (LTC)

Litecoin was created and launched in 2011 by the former Google employee Charles Lee (Coindesk, 2014). At the time, Litecoin had the second largest market cap and was called “The silver to Bitcoin’s gold” (Coindesk, 2014). Litecoin uses the same program coding as Bitcoin, which makes it possible to integrate the currency to already existing applications supported by Bitcoin, but with much faster transaction confirmations (Litecoin, 2018). The swift verification system enables Litecoin to be efficient even for small purchases (Litecoin, 2018). Today, Litecoin is the fifth largest cryptocurrency with a market capitalization of $7 935 million (2018-03-27) (CoinMarketCap, 2018).

Figure 1: USD-price development of Bitcoin, Ethereum, Ripple and Litecoin



This figure illustrates the USD-price development of the four chosen cryptocurrencies between 2015-08-10 and 2018-04-09. The y-axis for the individual graphs is described with the same range of values to visualize the different price levels of the cryptocurrencies.

2.2 Other terminology

2.2.1 Blockchain technology

The innovative blockchain technology is the foundation of cryptocurrencies. Nofer, Gomber, Hinz and Schiereck (2017) explain the blockchain as a series of data sets composed by a chain of blocks. Every block has a unique name or Hash value, contains data about previous transactions and is marked with both a timestamp and a random number (nonce) which is used as the verification code (Nofer et al., 2017). The history of all prior coin transactions is stored in the chain of blocks that starts with the coin owned by the creator of that specific block (Nakamoto, 2008). Miners, or nodes, create and validate the blocks by solving algorithms. They are rewarded with Bitcoins as an incentive to stay honest and avoid manipulation of the values (Nakamoto, 2008). As the ledger (blockchain) gets longer and more complicated, these algorithms take more time and power to solve (Bariviera et al., 2017).

The structure of the blockchain mitigates the risk of fraud since a modification of a block would require a change in the hash values of all the preceding blocks (Nakamoto, 2008). Furthermore, to validate and verify a transaction, a majority of the network of miners need to agree and approve the record of the previous transactions in the ledger. Possible fraudulent users would thus need to possess an enormous amount of computer power to reproduce all the hash values of old, as well as newly created, blocks to succeed with his or her malicious act (Nakamoto, 2008).

It has been stated that there are some scalability issues with the technology, since an increased number of blocks decreases the speed of confirmations, transactions and communication within the network (Nofer et al., 2017). The fully digital nature of the blockchain technology might also contribute to an increased possibility of theft through malware attacks. A great advantage, on the other hand, is the absence of intermediaries (central clearing houses for validation) which enables for transactions without a third party collecting data about the users (Nofer et al., 2017). In addition, it facilitates the trace of ownership, and allows the network to function properly even if some nodes break down (Nofer et al., 2017). The privacy offered, despite the publicly announced and verified transactions, is made possible by keeping the public verification keys anonymous (Nakamoto, 2008).

2.2.2 Fiat currency

Fiat currency is a standard currency backed by a sovereign government and declared to act as the medium of exchange in a specific country or region (Encyclopædia Britannica, 2018). Fiat currency is not backed by a commodity and does not have any intrinsic value, as during the days of the gold standard (Baur et al., 2017). Instead, the value stems from trust in the issuing government and its creditworthiness. There is usually a corresponding interest rate which is included in valuation models and macroeconomic theories (Glaser et al., 2014). Fiat currency can be seen as a means to reflect the current state of the economy and the monetary policy in the area where it is issued and used (Bariviera et al., 2017).

Moreover, standard currency and money is usually defined through three functions: (i) medium of exchange, (ii) accounting unit and (iii) store of value (ECB, 2012). Out of all the fiat currencies, the ones referred to as fiat currencies in this thesis are US Dollars (USD), Japanese Yen (JPY), South Korean Won (KRW) and Euro (EUR).

2.3 Problem description

Uncertainty in a financial context stems from various factors, such as large price movements and insufficient amount of information. When trading with novel securities, such as Bitcoin, Ethereum, Ripple and Litecoin, this uncertainty might reduce the possibility for cryptocurrencies to store value, and by that query their use as mediums of exchange in practice (Glaser et al., 2014). An observed example of this uncertainty is the volatility of one Bitcoin in the end of 2017, which reached its all-time high at $19 114 by the 18th of December, corresponding to a 2311% increase from one year prior to that date. The extreme increase in price was tightly followed by a 60% decrease in the subsequent weeks (CoinMarketCap, 2018). This kind of volatility in an asset is usually not associated with stable economy and can raise concerns regarding the use of cryptocurrencies as a substitute to standard, government-backed currencies. Moreover, cryptocurrencies lack a clear definition of their features and functions (Bariviera et al., 2017), which have led to the discussion on whether they are to be seen as currencies or speculative investments. To mitigate this uncertainty and facilitate trade, more research needs to focus on the characteristics of these assets and examine what primarily drives the return of cryptocurrencies.

The popularity of Bitcoin among private investors in recent years has raised the interest of trading in other cryptocurrencies as well. Its popularity, coupled with the inadequate information about its characteristics, has possibly led to an overconfidence in the opportunity to acquire great returns from trading with cryptocurrencies. There is, by definition, always risk and uncertainty in trading, but misconceptions and over-reliance on unexplored assets might result in substantial losses and even financial crises. Could it be that, after adjusting for risk, investors are better off holding a well-diversified stock portfolio rather than gambling with the high volatility of the market of cryptocurrencies?

2.4 Purpose and research questions

The main purpose of this thesis is to investigate which market indicators drive the price development of cryptocurrencies and from the results draw conclusions about their functions and features. The variables in focus will be categorized into macro-financials, factors of supply and demand and factors of attention.

The secondary purpose is to analyse the risk-adjusted return of Bitcoin, Ethereum, Ripple and Litecoin. Due to the great price movements, the excess return of cryptocurrencies might have been diminished. Thus, the objective is to conclude whether cryptocurrency returns have sufficiently compensated for the high volatility. Consequently, the research questions in this thesis are divided into the following two:

1. What drives the price development of cryptocurrencies?
2. Is the risk-adjusted return of cryptocurrencies higher or lower than the return of MSCI World Index?

The results of the first research question will contribute to a better understanding of the features of the cryptocurrency market as a whole, without the narrow focus on Bitcoin, and whether cryptocurrencies are comparable to fiat currencies or speculative investments. If the historical price development of the cryptocurrency market can be understood, it could reveal new information about these assets. The outcome of the second research question will state if cryptocurrencies historically have outperformed the market.

2.5 Theory and literature study

The scientific article of Bariviera, Basgall, Hasperué and Naiouf (2017), seeks to present some statistical characteristics of the Bitcoin market. Initially, they state that Bitcoin does not fulfill the main properties of a standard currency mentioned by ECB (2012), since it is barely accepted as a medium of exchange and has not shown near enough stability to be considered having the ability to store value. When examining the dynamics of the price market, they analyse the long- and short-term memory of Bitcoin, i.e. whether the price development is dependent on previous prices or not, using both hourly intraday prices and daily prices. Bariviera et al. conclude that more research should be done to understand the price dynamics of Bitcoin, and has served as a motive for this thesis.

Dyhrberg (2016) tries to classify what kind of financial asset Bitcoin is and gain an understanding for Bitcoin's position in portfolio and risk management. By comparing Bitcoin to the price of gold and USD, using GARCH to analyse its correlation of volatility, Dyhrberg classifies Bitcoin as something between gold and USD and hence useful in portfolio and risk management. The five-year period of data analysed in her scientific article ends in May 2015, only capturing two years of active trading in Bitcoin. Given her findings do not fully reflect the reality of recent Bitcoin trading, characterized by large price movements, there are reasons to analyse more up-to-date data.

Baur, Dimpfl and Kuck (2017) criticize the econometric models and GARCH used by Dyhrberg (2016), but agree on the subject being interesting and relevant. Initially they attempt to replicate the results from Dyhrberg's article by using the same data sample period and GARCH. They did not obtain the same results, but found that Dyhrberg seems to assume zero returns on weekends for the assets that are only traded during business days, compared to Bitcoin which is traded all day, every day. The second part is an updated version of the model, extending the sample and using more of a descriptive analysis to answer the research question. These results show that Bitcoin is very different from gold, which contrasts Dyhrberg's findings. Bitcoin is also very different from fiat currencies and cannot be used in portfolio and risk management in the way stated by Dyhrberg. Baur et al. point out that Bitcoin resembles a speculative asset due to its excessive returns. Hence, it is interesting to analyse the connections between Bitcoin and the stock market and consequently compare the risk-adjusted return with the market return.

Glaser, Zimmarmann, Haferhorn, Weber and Siering (2014) investigate the intentions of new users when changing from domestic currency to cryptocurrency, and attempt to understand Bitcoin by studying the characteristics and intentions of the buyers. Glaser et al. test for two general purposes when purchasing cryptocurrencies: either as an alternative, cross-border payment system, or as a speculative investment to capture favorable movements in price. They examine if Bitcoin events, both good and bad, are reflected in the price movements in line with the Efficient Market Hypothesis. Besides this, they focus on variables such as trading volume, number of network members and transactions within the network as well as to other units. Their results show that many new Bitcoin users treat it as an investment rather than a medium of exchange. Due to this speculative treatment of Bitcoin, it can be concluded from these findings that the price of cryptocurrencies might move according to, or be driven by, the stock market.

Blau (2018) tries to define some facts about the Bitcoin price dynamics and examines whether speculative trading in Bitcoin might be the cause of the observed volatility, since speculative trading commonly plays a role in the creation of asset bubbles. Using a benchmark of 51 other currencies, he observes that periods of high volatility did not, as a matter of fact, have a positive correlation with speculative trading. On the contrary, he found the coefficient for speculation to be negative, and could furthermore state that speculative trading did not contribute to the volatility of Bitcoin. Blau could not find a clear connection between speculation and volatility, and instead considers the idea that Bitcoin behaves more like a currency than a speculative investment, which contradicts the findings of Glaser et al. (2014). The conclusion of Blau therefore suggests that cryptocurrencies could be a substitute to fiat currencies.

When Ciaian, Rajcaniova and Kancs (2016) analysed the price information of Bitcoin, they used a more exhaustive model compared to Dyhrberg (2016) who only focused on macroeconomic indicators. By including data on supply and demand, macro-financial factors and appeal of Bitcoin for users, Ciaian et al. broadened the perspective in which to analyse the features of Bitcoin. The findings are somewhat in line with the results from Baur et al. (2017), suggesting that macro-financial factors do not have a significant effect on the price of Bitcoin. However, they found that demand factors, such as the number of transactions, have a strong impact on the price. Furthermore, the variable representing number of views on Wikipedia, an approximation of Bitcoin appeal, was found to have a positive effect during the first years of trading, but as Bitcoin became more established on the financial market, the significant effect disappeared. The study of Ciaian et al. has been an inspiration when selecting the categories of independent variables for the first research question.

The scientific article of Scholz and Wilkens (2005) deals with the puzzle of different risk-adjusted performance measures. They introduce a number of basic performance models, discuss the differences and problematize their use. The Modigliani and Modigliani measurement RAP (risk-adjusted performance), more known as the M^2, is introduced as a commonly used and accepted measurement for performance, providing a quota that estimates the risk-adjusted return in percentage terms. It uses the standard deviation as the measure of risk, which can be easily interpreted by investors. However, M^2 is based on the total risk of a specific asset, meaning that it suits investors who exclusively invest in one single fund or stock. This is a limitation with the M^2-measure according to Scholz and Wilkens. They further discuss the Sharpe ratio, probably the most widely used measure for risk-adjusted performance, which measures units of excess return generated per unit of risk denoted as standard deviation of excess return. In contrast to M^2, the Sharpe ratio provides a unit-based measurement (Scholz and Wilkens, 2005).

The above-mentioned research papers are used as support and inspiration for the selection of independent variables and configurations of the data regarding the first research question. The risk-adjusted measure best suited to answer the second research question is also motivated by previous research.

2.6 Limitations

An ongoing problem when examining a new financial phenomenon is the lack of historical data. Regarding Bitcoin and Litecoin, it is possible to collect data for a relatively long period (CoinMarketCap, 2018), which generates more reliable results. However, some limitations remain since reliable data for Ripple only can be found from 2013-08-05, and the most novel currency, Ethereum, only has observations going back to 2015-08-10 (CoinMarketCap, 2018).

Bitcoin Cash, as the fourth largest cryptocurrency in terms of market capitalization (2018-03-27) (CoinMarketCap, 2018), is excluded from the sample of cryptocurrencies since it was introduced in 2017. With less than a year of observations, the sample would not have provided enough information for analysis. Instead, the fifth largest cryptocurrency Litecoin is included in order to make the sample more exhaustive.

The observations of cryptocurrency prices collected from CoinMarketCap, hits on news collected from the Meltwater Platform, as well as page views on Wikipedia, are not limited to business days or trading hours. The financial data gathered from Bloomberg has this limitation, and therefore weekend observations from CoinMarketCap, Meltwater and Wikipedia are manually removed to match the data from Bloomberg.

3. Data and descriptive statistics

The sample of dependent and independent variables covers approximately two and half years, or 696 trading day observations (2015-08-10 to 2018-04-09). All time series data is provided in daily observations of five days trading weeks, from Monday to Friday. The first day with access to trading data on all four cryptocurrencies included, is 2015-08-10 (CoinMarketCap, 2018) and therefore the starting date of the sample.

3.1 Dependent variables

Bitcoin, Ethereum, Ripple and Litecoin, four of the five largest (market capitalization) cryptocurrencies, represents the sample and the united dependent variable used to draw conclusions about the whole cryptocurrency market. The total capitalization of the cryptocurrency market is $301 592 million (2018-03-27) (CoinMarketCap, 2018), and the sample accounts for $211 577 million (2018-03-27) (CoinMarketCap, 2018) which is equivalent to 70% of the total market. The raw data on Bitcoin, Ethereum, Ripple and Litecoin was gathered from CoinMarketCap (2018-04-09) in USD close price. Time series of each individual cryptocurrency is constructed

Table 1: Descriptive statistics of the dependent variables

Dependent variables	*N*	*mean*	*sd*	*min*	*max*
Bitcoin (USD)	696	2793	3960	211	19114
Ethereum (USD)	696	171	278	0,43	1300
Ripple (USD)	696	0,19	0,42	0,00	3,20
Litecoin (USD)	696	39	68	2,63	358

This table presents the descriptive statistics of the dependent variables included in the model, where column (N) is the number of observations, (mean) is the average value, (sd) is the standard deviation, and (min) and (max) show the minimum and maximum values respectively.

3.2 Independent variables

3.2.1 Macro-financials

According to the results of Glaser et al. (2014), new Bitcoin users seem to treat the cryptocurrency as more of a speculative investment than a currency. Consequently, the MSCI World Index, used by Baur et al. (2017), is included as an independent variable to capture possible driving forces from the global economy and the financial development. The MSCI World Index, a sample of stock market movements, represents 23 markets from developed countries, excluding emerging markets (MSCI, 2018). Considering that cryptocurrencies operate globally as payment systems (Bitcoin, 2018; Ethereum Project, 2018; Ripple, 2018; Litecoin, 2018), the regions included in the MSCI World Index are a well-suited sample of the operating market of cryptocurrencies. The MSCI World Index is also used as the market portfolio in the analysis of risk-adjusted return. Time series data of MSCI World Index is collected from Bloomberg in USD.

The findings of Dyhrberg (2016) revealed some statistical similarities between Bitcoin and gold, and Baur et al. (2017) further discussed the fundamental commonalities between the two assets. Similarities between gold and cryptocurrencies are features such as scarcity, expensive mining, not backed by any government, and de-centralization (Baur et al., 2017). Given the literature studies and the common features, gold price is an interesting variable to include in the model. The time series data for close price of gold (troy oz) is collected from Bloomberg in USD.

Oil price is included by Ciaian et al. (2016) as one of two macro-financial factors, and according to Palombizio and Morris (2012), oil price is one of the main motives for cost pressure, making it a leading indicator of inflation. Hence, when the oil price indicates potential changes in the general price level, it could lead to an appreciation or depreciation of cryptocurrency prices. To investigate whether there are any effects of oil price changes on cryptocurrency value, the WTI-index, which is the price of crude oil measured by West Texas Intermediate (Bloomberg, 2018), is included in the model as an independent variable. Time series data for WTI is collected from Bloomberg in USD per barrel.

According to the results of Blau (2018), speculation did not explain the volatility of Bitcoin. Instead he implies that there is a possibility of Bitcoin to be used more as a currency, hence fiat currencies are included as one of the macro-financials in the model. By identifying the markets with the highest transaction frequency of cryptocurrencies, the most essential and relevant fiat currencies are selected. According to CryptoCompare (2018), the four common fiat currencies with highest trading volume of Bitcoin, Ethereum, Ripple and Litecoin are Japanese Yen (JPY), US Dollar (USD), South Korean Won (KRW) and Euro (EUR). These selected mediums of exchange are included to detect possible effects of fiat currencies, as the real-life counterpart to cryptocurrencies. Moreover, the model might suggest which, if any, exchange rate the cryptocurrencies are more sensitive to. The time series of the exchange rates for EUR, JPY and KRW are denoted in USD, where the Korean Won is in USD per 100 KRW. The time series data is collected from the Bloomberg platform.

3.2.2 Supply and demand

According to Ciaian et al., (2016), the interaction between the market forces of supply and demand in the Bitcoin market is a key driver of Bitcoin price. The supply is mainly driven by the size of the cryptocurrency economy such as the market capitalization and number of crypto coins in circulation (Ciaian et al., 2016). Since market capitalization is strongly informative about the number of coins, the market capitalization of each cryptocurrency is the only supply factor in this thesis. The demand of cryptocurrencies is primarily driven by the value of cryptocurrencies as a medium of exchange and expectations of the value in the future (Ciaian et al., 2016). Trading volume for each cryptocurrency, representing investors' interests in the asset, is included as the factor of demand. Data on market capitalization denoted in USD, and trading volume denoted in number of traded coins, is collected from CoinMarketCap and weekend observations for the two variables are manually removed.

3.2.3 Attention

Glaser et al. (2014) state that information from any available source will facilitate the valuation of cryptocurrencies for users and investors. This information can come from social media, news articles or other communities, both online and in real life. In their research paper, Glaser et al. (2014) use hits on English Bitcoin Wikipedia as an approximation for user attention and hype. Information from these different sources is likely to influence the prices of cryptocurrencies due to the absence of corresponding interest rates (Glaser et al., 2014).

In this thesis, two variables are included to reflect attention. The first one is the number of views on the Wikipedia page for each individual cryptocurrency, collected from the Wikipedia Pageview Analysis tool which presents views-per-page statistics. The second variable is gathered from a platform for Social Media and News Monitoring provided by the Media Intelligence company Meltwater. This variable counts the number of times at least one of the words *Bitcoin*, *Ethereum*, *Ether*, *Litecoin*, *Ripple*, *Cryptocurrency* or *Cryptocurrencies* has been mentioned in news articles online. The data is matched by manually removing weekend observations.

3.2.4 Control variables

To control for the risk-free rate and the macroeconomic state, the three-month US Treasury bill rate is included in the model as a control variable. The time series for the T-bill rate is collected as a percentage from Bloomberg and transformed into decimals. No other transformations are made to the T-bill rate.

Table 2: Descriptive statistics of the independent variables

Independent variables	*N*	*mean*	*sd*	*min*	*max*
MSCI (USD)	696	1811	180	1469	2249
Gold (USD)	696	1240	78	1051	1366
WTI Oil (USD)	696	48	8	26	66
USD/100KRW	696	0,088	0,003	0,080	0,095
USD/EUR	696	1,128	0,051	1,039	1,251
USD/JPY	696	0,009	0,000	0,008	0,010
Trading volume Bitcoin (coins)	696	1910600672	3908527392	17254100	23840900000
Trading volume Ethereum (coins)	696	640803021	1315372031	109567	9214950000
Trading volume Ripple (coins)	696	296157196	971825573	77796	9110440000
Trading volume Litecoin (coins)	696	215005574	516702777	507480	6961680000
Market Cap Bitcoin (USD)	696	46225835489	66670394144	3053250000	320242000000
Market Cap Ethereum (USD)	696	16357380114	27214521045	31973600	132404000000
Market Cap Ripple (USD)	696	7463589109	16274604541	137194000	130302000000
Market Cap Litecoin (USD)	696	2109205145	3731137151	111133000	19525500000
Hits on News	696	5680	6794	453	30700
Bitcoin views on Wikipedia	696	26016	35424	6245	344686
Ethereum views on Wikipedia	696	4037	4272	333	30494
Ripple views on Wikipedia	696	92	131	18	1819
Litecoin views on Wikipedia	696	1352	2797	150	44211

This table presents the descriptive statistics of the independent variables included in the model, where column (N) is the number of observations, (mean) is the average value, (sd) is the standard deviation, and (min) and (max) show the minimum and maximum values respectively.

4. Method

For the remaining part of this thesis, an empirical, quantitative study will be performed to examine the linear relationship between the dependent and independent variables, as well as an analysis of the risk-adjusted return. The modelling and processing of the data is done in the data analysis and statistical software tool STATA 15.1.

4.1 Econometric models

The Ordinary Least Squares (OLS) regression, used as the fundamental method in this thesis, estimates coefficients based on the best linear relationship between the dependent and independent variables. The OLS-estimates are the best suited coefficients to measure the co-movement between variables, since they minimize the sum of the squared residuals (Wooldridge, 2014, p. 61).

Ordinary Least Square regression model

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k + U$$

The OLS-regression model best suited to answer the first research question in this thesis must possess the ability to analyse several dependent variables that vary over time. The four cryptocurrencies, as well as the independent variables, are thus sorted into a panel data structure and analysed through panel data models to draw conclusions about the whole cryptocurrency market. Panel data combines cross-sectional and time-series data into repeated cross-sectional data series (Wooldridge, 2014, p. 360). There are multiple approaches of panel data, such as the fixed effects model and the random effects model (Torres-Reyna, 2007).

The fixed effects model explores the relationship between the independent and dependent variables within an entity. The entity in this thesis is represented by the category of cryptocurrencies. The individual characteristics of each cryptocurrency might influence the independent variables, implicating a correlation between the error terms of the cryptocurrencies and the independent variables, a correlation reduced by the fixed effects model. The fixed effects model accounts for all individual characteristics to access the net effect of the independent variables (Torres-Reyna, 2007).

The random effects model assumes that there is no correlation between the independent variables and the error term of the entity, and therefore does not control for such effects (Torres-Reyna, 2007). This allows for time-invariant differences to play a role as explanatory variables.

The Hausman test is used to determine which of the random or fixed effects model is best suited to the panel data. It tests for whether the error terms (U_i) correlate with the independent variables. The null hypothesis in the Hausman test states the absence of such a correlation, meaning that the random effects model is preferred and that potential individual differences should be obtained as explanatory variables (Wooldridge, 2014, p. 399). According to the Hausman test in STATA 15.1 applied to the panel data (*Table 1,* appendix), the null hypothesis cannot be rejected and consequently, the random effect model is best suited out of the two.

The Breusch-Pagan Lagrange multiplier (LM) test is used to decide between the random effect model and simple OLS-regression, based on the variance within the entity. The null hypothesis states that there is no such variance (Torres-Reyna, 2007). According to the Breusch-Pagan Lagrange multiplier, there is no variance across the cryptocurrencies in the panel data (*Table 2*, appendix), implying no panel effect, hence the simple OLS-regression is best suited. This is shown since the same results are obtained from all three models, fixed effects, random effects and OLS-regression (*Table 1*, appendix and *Table 3*) but the absence of panel effect makes it irrelevant to use the fixed or random effects model to answer the research question.

An OLS-regression estimated with robust standard errors is called a robust-regression, where the squared residuals are reweighted (IDRE, 2017). To deal with heteroscedasticity in the data set, (shown in section 4.2.4), the robust-regression model (1) is used to measure the linear relationship between the dependent and independent variables. The null hypothesis states that all coefficients for macro-financial, supply-demand and attention are equal to zero. This will consequently be tested through the regression and its F-value, followed by an assessment of the p-values from the individual t-tests for the regression coefficients. The alpha or significance level is set to 0,05 in this thesis, meaning that there is a 5% probability of rejecting the null hypothesis when it is true (Wooldridge, 2014, p.100). In the robust-regression model for panel data (1), β_i is the coefficient for the variable i, delta (Δ) denotes the first difference in *ln*-values, where *ln* is the natural logarithm of the original values. The independent variables are MSCI World Index (*MSCI*), Gold price (*Gold*), WTI oil index (*WTI*), exchange rate for Euro (*USD/EUR*), exchange rate for Japanese Yen (*USD/JPY*), exchange rate for Korean Won (*USD/100KRW*), total volume of traded coins (*Volume*), total market capitalization of the cryptocurrencies (*MarketCap*), hits on news articles (*News*) and views on Wikipedia (*Wikipedia_Views*), and the dependent variable (*Cryptocurrencies*) is the four chosen cryptocurrencies in panel structure.

Robust-regression model for panel data

$$\begin{aligned}\Delta lnCryptocurrencies &\\ = \beta_0 &+ \beta_1 \Delta lnMSCI + \beta_2 \Delta lnGold + \beta_3 \Delta lnWTI + \beta_4 \Delta lnUSD/EUR + \beta_5 \Delta lnUSD/JPY \\ &+ \beta_6 \Delta lnUSD/100KRW + \beta_7 \Delta lnVolume + \beta_8 \Delta lnMarketCap + \beta_9 \Delta lnNews \\ &+ \beta_{10} \Delta lnWikipedia\_Views\end{aligned} \tag{1}$$

4.2 Transformation of data

Most of the independent variables presented in this thesis consist of positive, non-stationary daily financial observations. These variables need to be transformed before used in a regression to obtain reliable estimates without bias or invalid standard errors. The following transformations are implemented to obtain the robust-regression model for panel data, assigned to answer the first research question.

4.2.1 Time trends

A time trend is detected when there is a general decrease or increase in the time series of a data sample (Farago, 2018). When searching for time trends, the following regression model is used to test whether α_1, the coefficient of time (t), is significantly different from zero (Wooldridge, 2014, p.294). Accordingly, if the null hypothesis can be rejected, there is a time trend in the sample.

$y_t = \alpha_0 + \alpha_1 t + U_t$

$H_0 : \alpha_1 = 0$

$H_A : \alpha_1 \neq 0$

All but one of the independent variables demonstrated a positive time trend with α_1 being significantly different from zero (*Table 3*, appendix). When time trends exist, the estimates become biased and cannot be reliably interpreted (Farago, 2018). Consequently, to avoid omitted variable bias, variables containing time trends (y_t) are detrended by first including time as an independent variable (1) and then saving the detrended residuals ($\ddot{y}_t$) (2) (Wooldridge, 2014, p. 299).

$y_t = \alpha_0 + \alpha_1 t + U_t$ (1)

$\ddot{y}_t = y_t - \hat{\alpha}_0 - \hat{\alpha}_1 t$ (2)

4.2.2 Highly persistent variables

Highly persistent variables are common in financial data, since yesterday's price is likely to affect the price of today. Most observations gathered for this thesis are from financial data, and problems with highly persistent variables are of greatest importance. A time series is highly persistent if the first order autocorrelation is close to 1 or (-1) (Wooldridge, 2014, p. 322). For all variables containing time trends, the detrended residuals ($\ddot{y}_t$) are used when testing for highly persistent variables.

First order autocorrelation

Corr $(\ddot{y}_t, \ddot{y}_{t-1})$ or Corr (y_t, y_{t-1})

$y_t = \rho y_{t-1} + U_t$

If the first order autocorrelation is larger than 0,9 or (-0,9), meaning $|\rho| > 0{,}9$, the variable is typically defined as highly persistent, causing omitted variable bias (Farago, 2018). According to the above definition, the majority of variables are highly persistent (*Table 3*, appendix). Difference in price or number is commonly used to avoid inconsistent estimators which come from including highly persistent variables. Using difference in price or number when dealing with time series also solves for any linear time trends (Farago, 2018) and allows for a consistent interpretation of all estimates.

4.2.3 Natural logarithm

In favor of reliability and interpretation of the estimated results, the natural logarithm is used on all data and consequently the difference in prices or numbers, used to avoid highly persistent variables, are based on the natural logarithm values. The interpretation of the difference in *ln*-values is useful, since it is approximately equal to return and allows the coefficients to represent percentage changes in return instead of absolute changes (*Figure 1*, appendix), also called elasticity. Furthermore, by using the difference in *ln*-values, more normally distributed residuals are obtained from regression model (1) compared to a model based on the difference in price or number without the use of the natural logarithm (*Figure 2*, appendix). Normally distributed data is important because of the t-tests, and the test functions cannot become t-distributed without normally distributed input (Jaggia and Kelly, 2016, p. 537). Therefore, the relatively normally distributed residuals from regression model (1) (*Figure 2*, appendix) implicate an appropriate model and reasonable estimates.

Difference in ln-value

$$\Delta ln(y_t) = ln(y_t) - ln(y_{t-1})$$

$$\Delta ln(y_t) \approx \frac{y_t - y_{t-1}}{y_{t-1}}$$

4.2.4 Heteroscedasticity

If the variance in the error term can be explained by the independent variables, there is a problem with heteroscedasticity causing invalid standard errors in the model (Wooldridge, 2014, p. 213). Possible heteroscedasticity in the regression model can be detected using the White test (Wooldridge, 2014, pp. 223-224). The first step is to save the residuals (U_t) from regression (1), estimated without robust standard errors, and the second step is to use the variance of the saved residuals (U_t^2) as the dependent variable to examine whether the independent variables are informative about this variance. The F-value confirms heteroscedasticity, since at least one of the coefficients for the variables explaining the variance is statistically different from zero (*Table 4*, appendix). Therefore, regression (1) is estimated with robust standard errors in STATA 15.1.

4.2.5 Serial correlation

Corr $(U_t, U_{t-h} \mid X_{t1}, \dots, X_{tk})$ or simplified as Corr (U_t, U_{t-1}) is equal to zero if there is no serial correlation in the error of the first lag (Farago, 2018). Serial correlation in error causes the statistical interpretation to be incorrect and sometimes misleading (Wooldridge, 2014, p.349). It can be detected by using the simplified model mentioned above, which for regression model (1), estimated with robust standard errors, shows a correlation of $-0{,}147$ (*Table 5*, appendix). However, considering the number of observations and the relatively low correlation, serial correlation is not a problem for the estimates.

4.3 Risk-adjusted return

There are multiple methods and models available to assess whether an investment generates sufficient return in comparison to its risk (Scholz and Wilkens, 2005). The most widely used measure is the Sharpe ratio which analyses how much excess return an investor receives per unit of risk, where risk is measured as the standard deviation (Simons, 1998). An investment with a high Sharpe ratio implies a higher return for a given level of risk, than for an investment with a lower ratio.

Since the Sharpe ratio is somewhat difficult to interpret without a benchmark, Modigliani and Modigliani expanded it to the Modigliani-Measure (RAP) or M^2 in 1997 (Simons, 1998). Instead of providing a unit-based measure, M^2 allows for a comparison with the benchmark (MSCI World Index) in percentage terms, enabling a more intuitive interpretation (Simons, 1998). This measure is used to answer the second research question.

The risk-adjusted return will be analysed both annually and monthly of 20 trading days, and the hypothesis suggests a lower, risk-adjusted cryptocurrency return due to the high volatility compared to MSCI World Index.

Modigliani-Measure, RAP (M^2)

$$M^2 = \left(\frac{\sigma_m}{\sigma_p}\right)\left(R_p - R_f\right) + R_f$$

$R_p - Return\ on\ asset$

$R_f - Risk\ free\ rate$

$\sigma_p - Standard\ deviation\ of\ return\ on\ asset$

$\sigma_m - Standard\ deviation\ of\ return\ on\ market\ portfolio$

Depending on the chosen start date for the calculated period, there is a risk that results obtained from the M^2-calculation fluctuate only because of the asset price on that specific day. To remove this uncertainty, MSCI World Index, the risk-free three-month T-bill rate and cryptocurrency prices are transformed into a 20-day sliding average. From this, both the monthly (20 trading days) and yearly risk-adjusted returns are calculated, while the standard deviation for the period is estimated from the daily returns.

The RAP, or M^2-measure, is only accurate if investors exclusively invest in one asset (Scholz and Wilkens, 2005), or in this thesis, one of the cryptocurrencies. Given that no other investment options, or their risk, are of interest for the research question, M^2 is an appropriate measure for the risk-adjusted return in this study.

5. Results and discussion

5.1 Results – Price development drivers

The null hypothesis, stating that all coefficients are zero, can be rejected at the prespecified significance level of 0,05 according to the F-value (*Table 3*) meaning, at least one of the variables in the model can be used to explain the price movements of the cryptocurrencies. Furthermore, in the individual assessment, four out of ten coefficients are individually significant at an alpha of 0,05 (*Table 3*).

Among the independent variables representing macro-financials, none of the coefficients are individually significant at the prespecified alpha of 0,05. Both coefficients within the category of supply and demand have individually significant effects at the significance level of 0,05. The coefficient for supply shows how a Market Cap increase of one percent corresponds to an approximate 0,26% value increase of cryptocurrencies. The coefficient for demand is 0,032 which implies that a percentage increase in Trading Volume leads to an approximate 0,03% increase in the price development of cryptocurrencies. The coefficients of the attention category are both individually significant at an alpha of 0,05. The coefficient for Views on Wikipedia is positive, while the coefficient for Hits on News is negative.

Table 3: Results from the robust panel regression of the cryptocurrencies.

Cryptocurrencies	*Coefficient*	*Robust Std. Err.*	*t-value*	*p-value*
MSCI	0,139	0,252	0,55	0,581
Gold	0,315	0,211	1,50	0,135
WTI oil	-0,042	0,057	-0,75	0,455
USD/EUR	-0,185	0,308	-0,60	0,549
USD/JPY*	-0,462*	0,259*	-1,79*	0,074*
USD/100KRW	0,356	0,296	1,20	0,230
Trading Volume***	0,032***	0,004***	7,73***	0,000***
Market Cap***	0,255***	0,036***	7,06***	0,000***
Hits on News**	-0,010**	0,005**	-2,2**	0,028**
Views on Wikipedia***	0,029***	0,007***	3,95***	0,000***

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.
R^2 (0,1534)
Prob > F = 0,000

This table presents the results from the robust-regression model (1) answering research question one. The column (Coefficient) describes the estimated coefficients β_i of the variables, (Robust Std. Err) presents the obtained standard errors and (t-value) and (p-value) show the t-statistics and p-values used to determine the significance of the individual variables. The F-test of the regression together with the R-squared is shown in the bottom left corner.

5.2 Results – Risk-adjusted return

The results from the M^2-analysis of the risk-adjusted return disprove the hypothesis that the return of MSCI World Index would be higher than the risk-adjusted return for each of the four cryptocurrencies (*Table 4*, *Figure 2*). The exceptions are Ripple in period one and Ethereum in period three, showing lower risk-adjusted returns than the return of the market portfolio. Compared to the market index, the risk-adjusted returns of the cryptocurrencies are considerably higher during the first two years of the sample, according to *Table 4*. On the other hand, last year has shown a more modest development, especially for Ethereum which only reached a risk-adjusted return of 4,9%, compared to the MSCI return of 6,8%.

Table 4: Annual risk-adjusted return in %

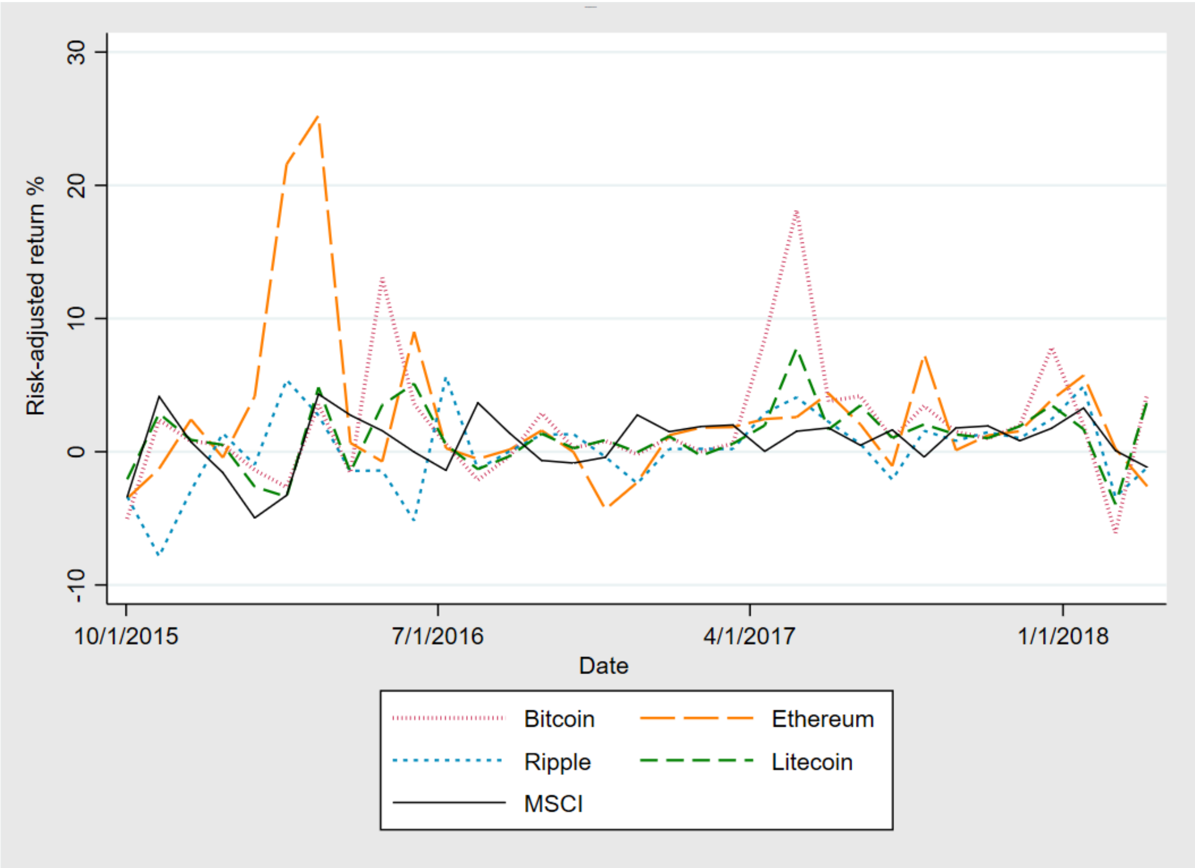
Risk-adjusted return (%)	*Bitcoin*	*Ethereum*	*Ripple*	*Litecoin*	*MSCI*
2015-09-07 to 2016-09-06	35,7	58,3	-3,7	39,5	3,9
2016-09-07 to 2017-09-06	52,6	86,6	66,6	57,5	12,4
2017-09-07 to 2018-04-09*	7,5	4,9	8,2	8,5	6,8

Note: * Incomplete year.

This table presents the yearly outcome from the M^2-measure for each Cryptocurrency and the MSCI World Index (Market portfolio). The dates of the yearly intervals are stated in column 1

The monthly (20 trading days) risk-adjusted return is for the majority of the period, more in line with the return of MSCI World Index compared to the annual analysis but with a few exceptions (*Figure 2*).

Figure 2: Monthly risk-adjusted return in %



This table illustrates the monthly outcome from the M^2-measure for each Cryptocurrency and the MSCI World Index (Market portfolio) with the monthly intervals of 20 trading days starting from 2015-09-07. The description of each line is stated in the figure.

5.3 Discussion – Price development drivers

Cryptocurrencies were created and launched with the intention of being independent from central authorities and governments (Nakamoto, 2008). The findings in this thesis show that none of the coefficients for the selected fiat currencies in the model are significant at an alpha of 0,05, suggesting that either the cryptocurrency system has succeeded in creating a completely stand-alone monetary system, or the cryptocurrencies are not used as counterparts to traditional currencies. Given that none of the coefficients of the other macro-financials appear to have any significance in the model, it can be assumed that cryptocurrencies do not follow the movements of traditional macro-financial factors, which is also the general conclusion based on the literature study. Considering this absence of correlation with the macro-financial variables, cryptocurrencies could have an interesting part to play in portfolio management as a hedging instrument. With regards to the initial comments about the characteristics, the findings indicate that cryptocurrencies cannot replace traditional mediums of exchange since there is no correlation between the cryptocurrencies and fiat currencies in this thesis, and according to Bariviera et al. (2017), Bitcoin does not fulfil all requirements of a currency. Hence, cryptocurrencies lean more towards speculative investments, but given that the price movements do not follow the market portfolio, buying cryptocurrencies cannot be seen as a direct substitute for investing in the stock market.

The positive effect from the trading volume implies that a higher demand increases the return, and the coefficient of market capitalization suggests that an increase in supply also increases the return. Can it be that both supply and demand have significant positive effects on the return, or is one, or both, of the variables rather driven by the price development of the cryptocurrency market? According to Ciaian et al. (2016), the size of the Bitcoin economy and number of transactions have strong significant impact on Bitcoin price, but they address no concern regarding causality. A possible explanation to the positive relationship between return and market capitalization is the Law of Supply; higher price will lead to an increase in supply (Frank and Cartwright, 2013, p.23), which implicitly state that supply is driven by the price development and not the other way around. Causality regarding demand and supply will need further investigation in order to fully explain how trading volume and market capitalizations relates to the price development. However, both are positive and significant, meaning that cryptocurrency prices have increased with both the size of the cryptocurrency market and the volume of traded coins. Since the number of Bitcoins will discontinue to grow from year 2140 (Bariviera et al., 2017), the findings suggest that, supposing there is still an active market for cryptocurrency trading, the demand will continue to drive the prices in a positive direction after the mining has ceased. However, it is important to keep the inherent connection between Market Cap and cryptocurrency prices in mind when evaluating the results.

Due to the massive media coverage on cryptocurrencies and their popularity among private investors, publicly available written information about these assets seems to have had an impact on the return, according to the results. Private investors interested in buying cryptocurrencies and wanting easy access to information might, for example, turn to Wikipedia on these grounds. The positive coefficient of Views on Wikipedia could therefore justify that an increase in page views indicates a growing demand for cryptocurrencies and a subsequent increase in price. Hits on News, on the other hand, presents the more journalistic, investigative take on attention and information. The news written in different articles do not need to be in a positive context. On the contrary, based on the negative sign of the coefficient, news articles about cryptocurrencies seem to be in a negative tone, meaning that more of these news articles lower the price on cryptocurrencies. Both Glaser et al. (2014) and Ciaian et al. (2016) could state a positive relationship between available information and price of cryptocurrencies. However, with Wikipedia as the only source included in their studies, the positive effect from available information does not fully reflect the category. The effect from Hits on News emphasizes the significance of attention, but indicates that the sign of the effect depends on the type of information source. Whether it is attention factors that drive the price development or the other way around will need further investigation.

5.4 Discussion – Risk-adjusted return

According to the results, cryptocurrency investors have been better off than investors of the market portfolio for the past two and a half years, despite the volatility. Whether the price development seen in the past years is the rise before a possible stabilization cannot be disregarded, and could in such case conclude in a lower risk-adjusted return in the future. The results of the monthly risk-adjusted returns are more volatile, possibly caused by the shorter time period. Even though the majority of the monthly observations are above the return of the MSCI World Index, there are still negative returns. In hindsight, it seems to have been more beneficial to hold cryptocurrencies over a longer time-period when trying to obtain high risk-adjusted returns, since the monthly effect has been more of a gamble.

5.5 Robustness analysis

5.5.1 Individual analysis

Although the main purpose of this thesis is to investigate the overall cryptocurrency market by treating Bitcoin, Ethereum, Ripple and Litecoin as equals, it does not account for the differences between these cryptocurrencies, which make it interesting to further investigate the characteristics of each individual currency. Factors such as difference in properties, size, and time of existence might lead to other results when analysing each cryptocurrency separately. For this robustness section, the same independent variables as in the main model (1) are used to explain the difference in *ln*-price, or in other words return, for each cryptocurrency individually. All induvial regressions are estimated with robust standard errors.

Bitcoin, as the number one cryptocurrency both in size (CoinMarketCap, 2018) and in popularity (Wikipedia, 2018) is, according to the results in *Table 6* (appendix), highly independent from external events. Due to the great Bitcoin market share, it could be expected that, out of the four cryptocurrencies in this thesis, Bitcoin is the least likely to be explained by the included variables. And considering the low R^2, the regression of Bitcoin is not informative of the price movements to any greater extent. However, the variable of Market Cap does have a significant effect, which indicates that supply is one possible driver of Bitcoin return.

$$\begin{aligned}\Delta lnBitcoin = \beta_0 &+ \beta_1 \Delta lnMSCI + \beta_2 \Delta lnGold + \beta_3 \Delta lnWTI + \beta_4 \Delta lnUSD/EUR + \beta_5 \Delta lnUSD/JPY \\ &+ \beta_6 \Delta lnUSD/100KRW + \beta_7 \Delta lnVolume + \beta_8 \Delta lnMarketCap + \beta_9 \Delta lnNews \\ &+ \beta_{10} \Delta lnWikipedia\_Views \end{aligned} \tag{2}$$

The individual study of Ethereum showed that both supply and demand are positive and significant at a 0,05 level (*Table 7*, appendix), indicating that Trading Volume and Market Cap are variables with a positive, linear relation with the price movements of Ethereum. Ethereum is only valid on its own platform (Ethereum Project, 2018) and could therefore be more sensitive to its own supply and demand, which is in line with these findings. Furthermore, Ethereum seems to be independent from both the macro-financials and the attention factors, since neither of these variables are significant at a 0,05 level.

$$\begin{aligned}\Delta lnEthereum = \beta_0 &+ \beta_1 \Delta lnMSCI + \beta_2 \Delta lnGold + \beta_3 \Delta lnWTI + \beta_4 \Delta lnUSD/EUR + \beta_5 \Delta lnUSD/JPY \\ &+ \beta_6 \Delta lnUSD/100KRW + \beta_7 \Delta lnVolume + \beta_8 \Delta lnMarketCap + \beta_9 \Delta lnNews \\ &+ \beta_{10} \Delta lnWikipedia\_Views \end{aligned} \tag{3}$$

The results from the regression of Ripple reflect the estimates obtained from the main study on the cryptocurrency market, by providing the same significant variables (*Table 8*, appendix). Considering that both fiat currencies and Ripple can be transferred through the Ripple network (Ripple, 2018), it could be expected that Ripple should be affected by macro-financial indicators, but according to the findings in this thesis, no such connections exist. Furthermore, the swift transaction system should enable Ripple to function as a useful medium of exchange, but no similarities with traditional currencies are found in the results either.

$$\begin{aligned}\Delta lnRipple = \beta_0 &+ \beta_1 \Delta lnMSCI + \beta_2 \Delta lnGold + \beta_3 \Delta lnWTI + \beta_4 \Delta lnUSD/EUR + \beta_5 \Delta lnUSD/JPY \\ &+ \beta_6 \Delta lnUSD/100KRW + \beta_7 \Delta lnVolume + \beta_8 \Delta lnMarketCap + \beta_9 \Delta lnNews \\ &+ \beta_{10} \Delta lnWikipedia\_Views\end{aligned} \tag{4}$$

Litecoin, also called “the silver to Bitcoin’s gold” (Coindesk, 2014), is basically a smaller version of the largest cryptocurrency. Considering the many similarities between Litecoin and Bitcoin, the driving factors of the price development should be, to some extent, equal for both cryptocurrencies. According to the findings in *Table 9* (appendix), Litecoin has the same significant variables as the cryptocurrency market, while Market Cap is the only common factor with the results of Bitcoin. Litecoin is smaller and could therefore be more sensitive to Hits on News and Views on Wikipedia, which is the greatest difference in comparison with the other results.

$$\begin{aligned}\Delta lnLitecoin = \beta_0 &+ \beta_1 \Delta lnMSCI + \beta_2 \Delta lnGold + \beta_3 \Delta lnWTI + \beta_4 \Delta lnUSD/EUR + \beta_5 \Delta lnUSD/JPY \\ &+ \beta_6 \Delta lnUSD/100KRW + \beta_7 \Delta lnVolume + \beta_8 \Delta lnMarketCap + \beta_9 \Delta lnNews \\ &+ \beta_{10} \Delta lnWikipedia\_Views\end{aligned} \tag{5}$$

The robustness analysis provides a deeper understanding of how the results of the four cryptocurrencies differ based on their individual qualities. The results from these differences might indicate a possible limitation in analysing Bitcoin, Etherum, Rippel and Litecoin as a united variable for the purpose of understanding the whole cryptocurrency market.

6. Conclusion

When price properties and characteristics of Bitcoin alone have been examined in the literature studies, no unified conclusion has been stated. Benchmarks such as gold, fiat currencies, and stock market indices are included to carry out the studies, but separately and never together as an exhaustive unit.

Although Bitcoin has been, and still is, the largest cryptocurrency in terms of both market capitalization and recognition, the cryptocurrency market has expanded and now offers more than one thousand alternatives. In this thesis, we sought to explain what drives the price development concerning the overall cryptocurrency market by including four of the five largest cryptocurrencies in market capitalization.

None of the macro-financials included had any significant effect, while the supply-demand variables, as well as the attention variables, were significant at an alpha of 0,05. This is in line with the statement of Glaser et al. (2014), implying that the absence of a corresponding interest rate leaves the users to determine the value for themselves. It is worth noting that the coefficient for Hits on News was negative, suggesting that articles written about cryptocurrencies are mostly in a negative tone, while the positive coefficient of Views on Wikipedia implies that eager investors turn to Wikipedia with the intention of accessing more information.

The findings in this thesis are interesting to analyse collectively; the absence of correlation with the fiat currencies, together with the lack of ability to store value (Bariviera et al., 2017), opposes the suitability of replacing fiat currencies with cryptocurrencies. Consequently, cryptocurrencies are more of a speculative investment. In addition, the fact that the price development is mainly driven by "soft factors" such as attention and less by economic and financial factors, means that cryptocurrencies have a low market risk, but a high idiosyncratic risk. This puts cryptocurrencies in an interesting position as a hedging instrument.

For the second research question, we could disprove the hypothesis regarding the risk-adjusted return of cryptocurrencies. We found that, initially, the returns for all cryptocurrencies, except Ripple, were higher than the benchmark, while they leveled out later on, approaching the size of the market portfolio return. According to these findings, investors have received greater returns by investing in cryptocurrencies than they would have by holding the market portfolio.

Ten years ago, cryptocurrencies did not exist. Scholars and investors are dealing with completely new and unfamiliar assets and are thus struggling to understand the characteristics of cryptocurrencies. We contribute to the literature on cryptocurrencies by suggesting that price development of cryptocurrencies is mainly driven by factors of attention as well as supply and demand. We also state that the risk-adjusted return has been higher than the market return, especially in a long-term perspective. Furthermore, we propose that more research should be done to examine the cryptocurrency market as a unified phenomenon, and in doing so, move away from the narrow focus on Bitcoin.

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8. Appendix

Table 1: The Hausman test

	Coefficients			
Hausman test	(b) *Fixed*	(B) *Random*	(b-B) *Difference*	sqrt(diag(V_b-V_B)) *S.E.*
MSCI	0,13950	0,13917	0,00033	0,00671
Gold	0,31552	0,31541	0,00011	0,00575
WTI oil	-0,04227	-0,04222	-0,00005	0,00164
USD/EUR	-0,18477	-0,18470	-0,00007	0,00829
USD/JPY	-0,46139	-0,46165	0,00026	0,00808
USD/100KRW	0,35603	0,35625	-0,00022	0,00788
Trading Volume	0,03220	0,03221	-0,00001	0,00007
Market Cap	0,25479	0,25517	-0,00038	0,00061
Hits on News	-0,01003	-0,01004	0,00001	0,00011
Views on Wikipedia	0,02937	0,02935	0,00001	0,00017

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic
chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 0,39
Prob>chi2 = 1,0000

This table presents the differences between the Random and Fixed effects model. The high Prob>chi2 indicates an absence of correlation between the error term and the independent variables.

Table 2: Breusch-Pagan Lagrange multiplier (LM)

y[cryptocurrencis,date] = Xb + u[cryptocurrencies] + e[cryptocurrencies,date]

LM test	*Var*	*sd=sqrt(Var)*
y	0,0056	0,0746
e	0,0047	0,0688
u	0,0000	0,0000

Test: Var(u) = 0

chibar2(01) = 0.00

Prob > chibar2 = 1.0000

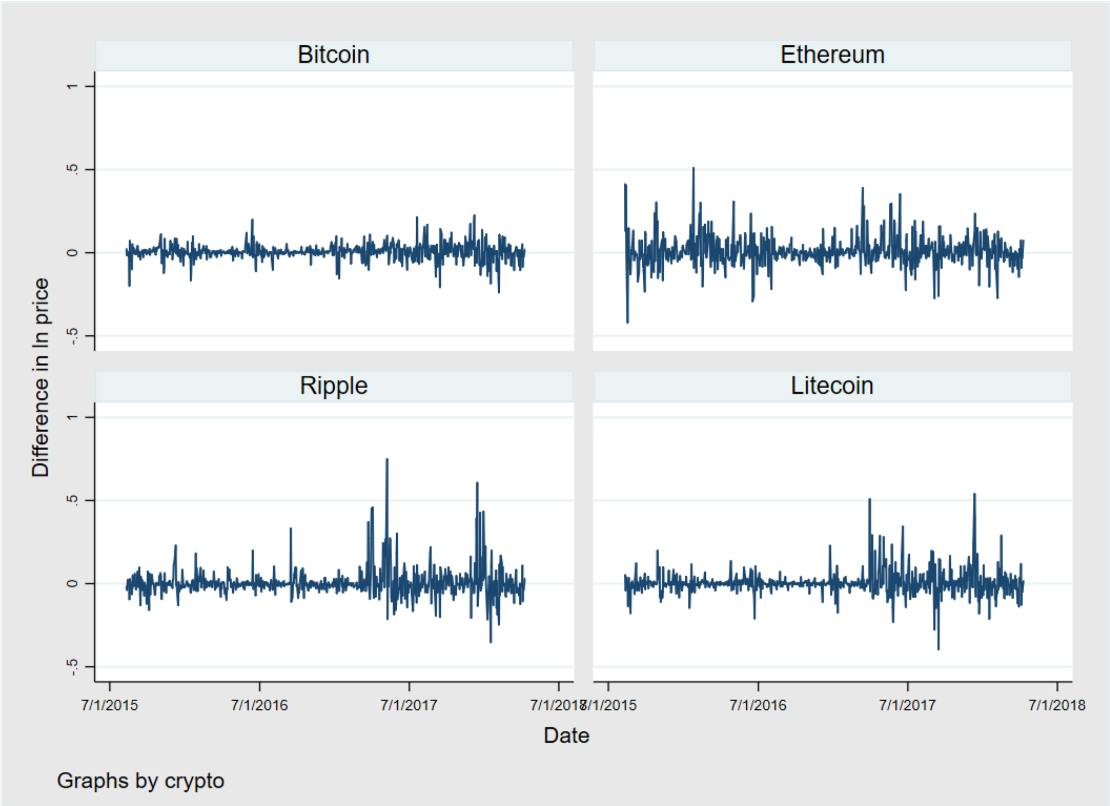
This table presents the difference in variance within the entity for the random effect model and a simple OLS-regression. The high Prob>chibar2 indicates no variance within the cryptocurrencies.

Table 3: Detection of time trend and highly persistent variables

Variables	*Time trend*	*Highly persistent*	*Corr (ÿt, ÿt-1)/Corr (yt, yt-1)*
Bitcoin	Yes	Yes	0,99
Ethereum	Yes	Yes	0,99
Ripple	Yes	Yes	0,98
Litecoin	Yes	Yes	0,99
MSCI	Yes	Yes	0,98
Gold	Yes	Yes	0,99
WTI oil	Yes	Yes	0,98
USD/EUR	Yes	Yes	0,99
USD/JPY	No	Yes	0,99
USD/100KRW	Yes	Yes	0,98
Hits on News	Yes	No	0,89
Market Cap Bitcoin	Yes	Yes	0,99
Market Cap Ethereum	Yes	Yes	0,99
Market Cap Ripple	Yes	Yes	0,98
Market Cap Litecoin	Yes	Yes	0,99
Trading volume Bitcoin	Yes	Yes	0,94
Trading volume Ethereum	Yes	Yes	0,90
Trading volume Ripple	Yes	No	0,79
Trading volume Litecoin	Yes	No	0,74
Bitcoin views on Wikipedia	Yes	Yes	0,92
Ethereum views on Wikipedia	Yes	No	0,83
Ripple views on Wikipedia	Yes	No	0,87
Litecoin views on Wikipedia	Yes	No	0,86

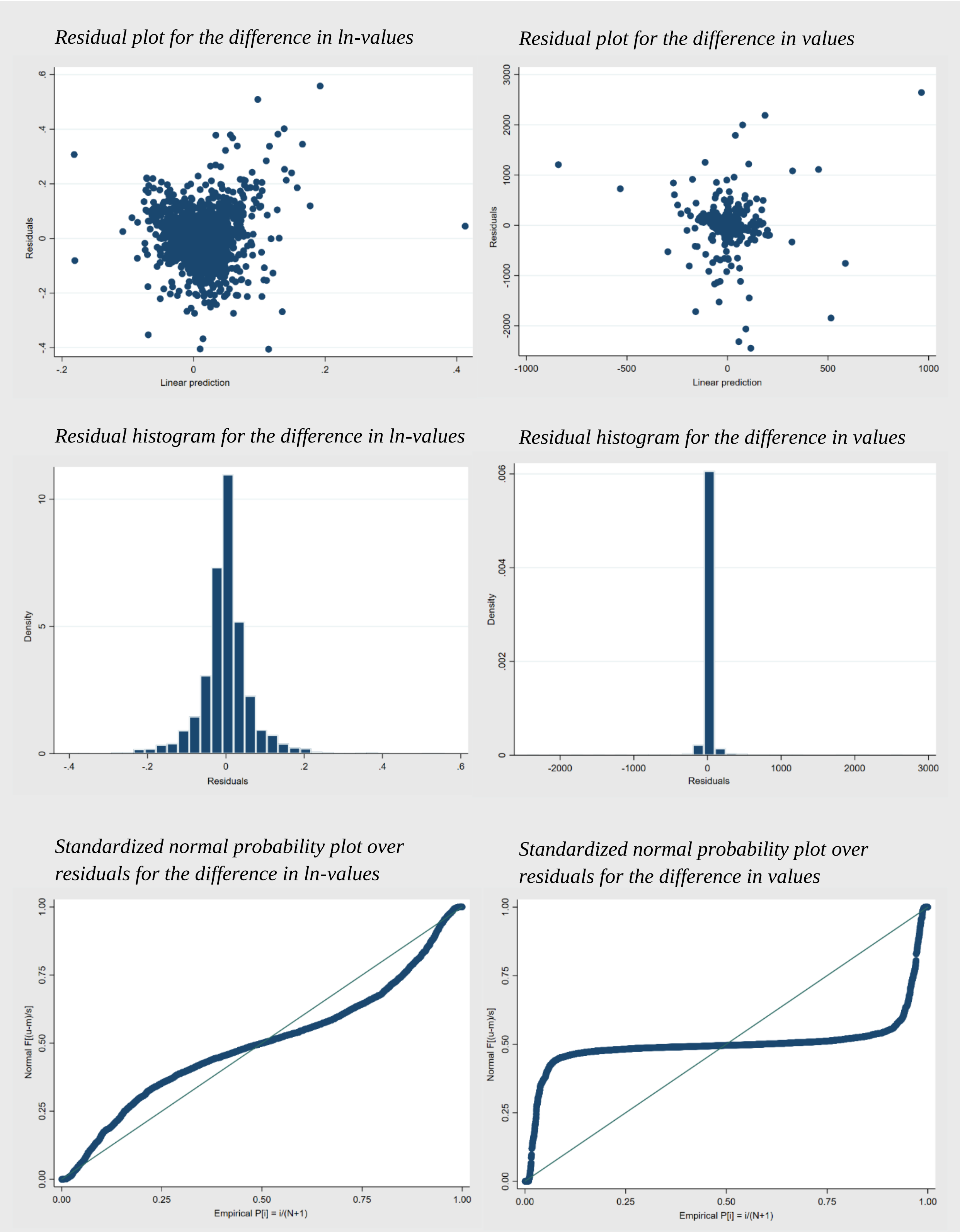
An overview of the results when controlling for time trend and high persistency. The Time Trend column indicates whether there is a time trend or not. The column Highly persistent indicates whether the variable is highly persistent or not, and the third column states the first autocorrelation.

Figure 1: The difference in natural logarithm (return) for the cryptocurrencies



These figures present the differences in values with natural logarithm, approximately equal to return, from 2015-08-10 to 2018-04-09, and is used as the dependent variable in robust-regression (1).

Figure 2: Graphs comparing the normal distribution of the linear regression model (1).



These three different plotted graphs illustrate that the use of natural logarithm (left column) provides more normally distributed residuals compared to not using natural logarithm (right column).

Table 4: Heteroscedasticity

U²	*Coefficient*	*Std. Err.*	*t-value*	*p-value*
MSCI	-0,031	0,050	-0,62	0,534
Gold	0,010	0,043	0,24	0,814
WTI oil	-0,009	0,012	-0,71	0,480
USD/EUR	0,007	0,062	0,11	0,911
USD/JPY	-0,003	0,060	-0,05	0,958
USD/100KRW	-0,033	0,059	-0,55	0,580
Trading Volume***	0,007***	0,001***	12,48***	0,000***
Market Cap***	0,021***	0,003***	6,10***	0,000***
Hits on News**	-0,002**	0,001**	-2,29**	0,022**
Views on Wikipedia***	0,005***	0,001***	3,92***	0,000***

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.
R^2 (0,0942)
Prob > F = 0,000

This table presents the estimated results from the detection of heteroscedasticity. The variance in the error term from regression (1), estimated without robust standard error, is included as the dependent variable to examine whether the independent variables are informative about this variance.

Table 5: Serial correlation in error

Corr (Ut, Ut-1)	*Ut*	*Ut-1*
Ut	1,0000	
Ut-1	-0,1473	1,0000

This table shows the correlation of the error term in time t and error term in time t-1 from robust-regression (1) when controlling for serial correlation in error term.

Table 6: Results from the individual robust-regression of Bitcoin

Bitcoin	*Coefficient*	*Robust Std. Err.*	*t-value*	*p-value*
MSCI	-0,059	0,410	-0,14	0,885
Gold	0,181	0,242	0,75	0,453
WTI oil	0,024	0,068	0,36	0,719
USD/EUR	-0,130	0,414	-0,31	0,753
USD/JPY	-0,281	0,340	-0,82	0,410
USD/100KRW	0,412	0,399	1,03	0,303
Trading Volume	0,002	0,007	0,21	0,831
Market Cap***	0,201***	0,063***	3,17***	0,002***
Hits on News	0,000	0,005	0,00	0,999
Views on Wikipedia	0,010	0,009	1,21	0,226

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.
R^2 (0,0477)
Prob > F = 0,2421

This table presents the results from the individual robust-regression (2) of Bitcoin in the robustness section. The column (Coefficient) describes the estimated coefficients β_i, (Robust Std. Err) presents the obtained standard errors and (t-value) and (p-value) show the t-statistics and p-values. The F-test of the regression together with the R-squared is shown in the bottom left corner.

Table 7: Results from the individual robust-regression of Ethereum

Ethereum	*Coefficient*	*Robust Std. Err.*	*t-value*	*p-value*
MSCI	-0,036	0,604	-0,06	0,952
Gold	0,455	0,604	0,75	0,452
WTI oil	-0,225	0,166	-1,36	0,174
USD/EUR	0,140	0,754	0,19	0,853
USD/JPY	-1,084	0,695	-1,56	0,119
USD/100KRW	0,700	0,756	0,93	0,355
Trading Volume***	0,025***	0,008***	3,15***	0,002***
Market Cap***	0,295***	0,054***	5,49***	0,000***
Hits on News	-0,001	0,011	-0,07	0,937
Views on Wikipedia	0,033	0,021	1,55	0,121

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.
R^2 (0,1502)
Prob > F = 0,000

This table presents the results from the individual robust-regression (3) of Ethereum in the robustness section. The column (Coefficient) describes the estimated coefficients β_i, (Robust Std. Err) presents the obtained standard errors and (t-value) and (p-value) show the t-statistics and p-values. The F-test of the regression together with the R-squared is shown in the bottom left corner.

Table 8: Results from the individual robust-regression of Ripple

Ripple	*Coefficient*	*Robust Std. Err.*	*t-value*	*p-value*
MSCI	0,507	0,506	1,00	0,317
Gold	0,315	0,350	0,90	0,369
WTI oil	-0,085	0,099	-0,86	0,392
USD/EUR	-0,121	0,637	0,19	0,849
USD/JPY	-0,045	0,509	-0,09	0,929
USD/100KRW	0,308	0,605	0,51	0,611
Trading Volume***	0,043***	0,007***	6,35***	0,000***
Market Cap***	0,257***	0,045***	3,98***	0,000***
Hits on News*	-0,0173*	0,01*	-1,82*	0,069*
Views on Wikipedia**	0,023**	0,011**	2,08**	0,038**

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.
R^2 (0,2195)
Prob > F = 0,000

This table presents the results from the individual robust-regression (4) of Ripple in the robustness section. The column (Coefficient) describes the estimated coefficients β_i, (Robust Std. Err) presents the obtained standard errors and (t-value) and (p-value) show the t-statistics and p-values. The F-test of the regression together with the R-squared is shown in the bottom left corner.

Table 9: Results from the individual robust-regression of Litecoin

Litecoin	*Coefficient*	*Robust Std. Err.*	*t-value*	*p-value*
MSCI	0,154	0,463	0,33	0,740
Gold	0,326	0,376	0,87	0,387
WTI oil	0,084	0,091	0,92	0,356
USD/EUR	-0,567	0,63	-0,90	0,369
USD/JPY	-0,269	0,455	-0,59	0,555
USD/100KRW	-0,026	0,513	-0,05	0,959
Trading Volume***	0,033***	0,009***	3,79***	0,000***
Market Cap***	0,215***	0,077***	2,79***	0,005***
Hits on News**	-0,016**	0,008**	-2,14**	0,033**
Views on Wikipedia***	0,066***	0,017***	3,98***	0,000***

Notes: *** Significant at 1% level, ** significant at 5% level, * significant at 10% level.
R^2 (0,1753)
Prob > F = 0,002

This table presents the results from the individual robust-regression (5) of Litecoin in the robustness section. The column (Coefficient) describes the estimated coefficients β_i, (Robust Std. Err) presents the obtained standard errors and (t-value) and (p-value) show the t-statistics and p-values. The F-test of the regression together with the R-squared is shown in the bottom left corner.