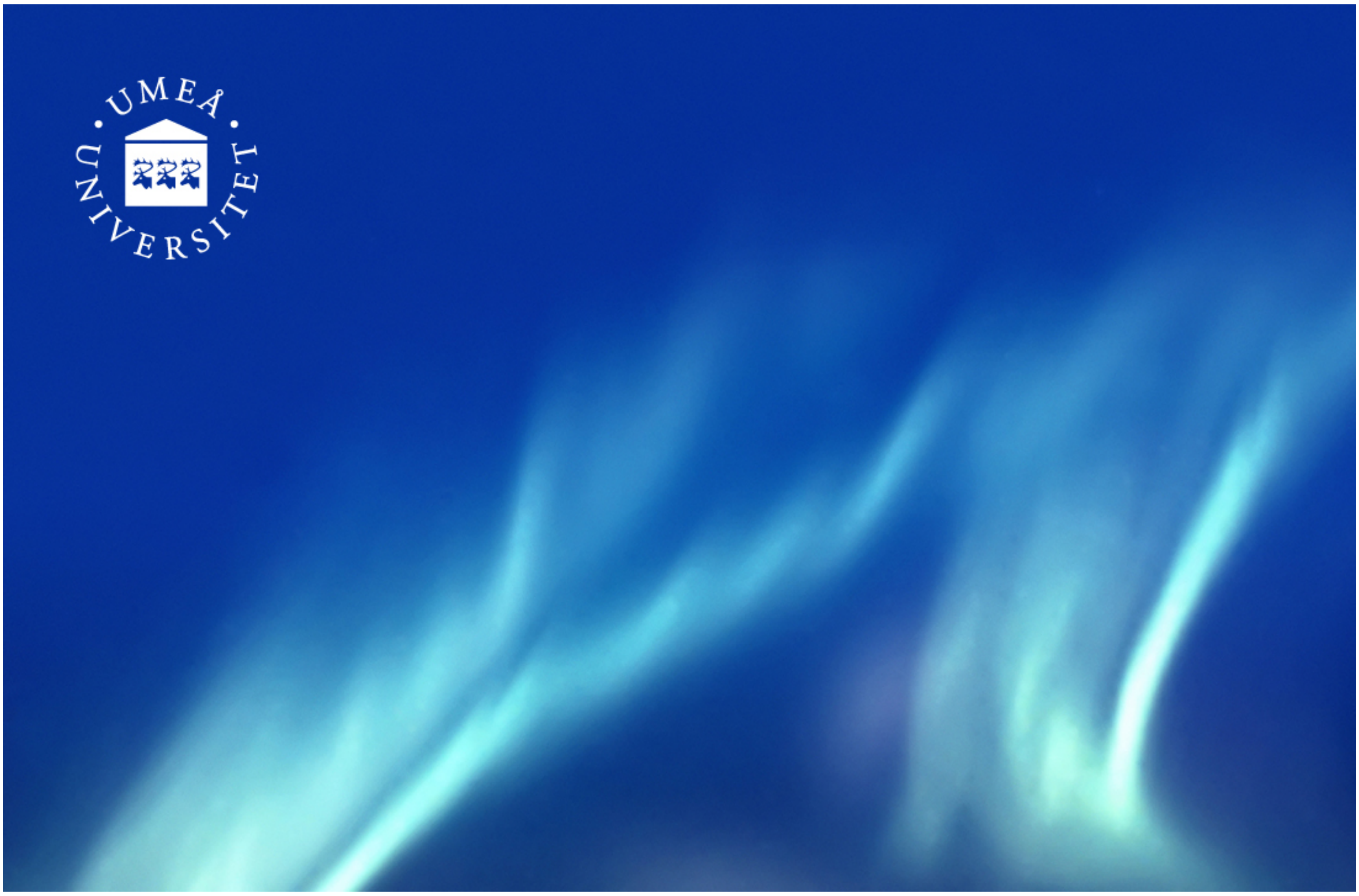

Cointegration among cryptocurrencies

A cointegration analysis of Bitcoin, Bitcoin Cash, EOS, Ethereum, Litecoin and Ripple

Joline Göttfert

Joline Göttfert
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Abstract

The purpose of this paper is to examine if there is cointegration between the daily closing price of the cryptocurrency Bitcoin and five other cryptocurrencies; Ethereum, Ripple, Bitcoin Cash, EOS and Litecoin in five different time periods, all ending April 9, 2019. To test if there is a long-run relationship between Bitcoin and these mentioned cryptocurrencies, two different tests for cointegration are applied; the Engle-Granger two step approach and Johansen's cointegration test as well as a Vector Error Correction Model (VECM). The results from both cointegration tests suggest that Bitcoin is cointegrated with Bitcoin Cash, Ethereum, Litecoin and Ripple. The Johansen test and the Engle-Granger method for cointegration demonstrate that Bitcoin and EOS do not have any cointegrating relationship. Another finding is that, based on the results from the VECM estimation, the price of Bitcoin has a statistically significant long-run impact on the prices of Bitcoin Cash, Ethereum, Litecoin and Ripple.

Keywords: Cointegration, cryptocurrency, Bitcoin, Johansen's test, Engle-Granger test, VECM

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1. Introduction

Cryptocurrencies are assets that are stored and exchanged digitally and eliminate the need for a trusted third party, like a government or a financial institution. Cryptocurrencies are designed to work as mediums of exchange, but due to high volatility some researchers argue that cryptocurrencies should be regarded as speculative assets (Baek and Elbeck 2015, Bação et al. 2018). They are not issued or controlled by any central authority and are maintained decentralized by a technology called blockchain. The blockchain is a distributed public ledger, which stores all the transactions. Since there is no third party involved, financial transactions are made secure by the use of strong cryptography (Dwyer 2015).

The evolution of cryptocurrencies has had an impact on the financial sector. The world is moving in the cashless direction and many stores in Sweden do not accept cash any more. Cryptocurrencies provide fast payments worldwide, with low transaction fees, which have made them attractive for persons who live under oppressive regimes (Gladstein 2018). Some countries, like Venezuela, have already launched their own cryptocurrency. Other countries, e.g. Sweden, are planning on issuing its own national digital currency (O'Neal 2018).

After Bitcoin was introduced in 2008 other alternative cryptocurrencies have emerged, which are called *altcoins* (alternatives to Bitcoin). As of today, there are more than 2000 different cryptocurrencies with various functions according to Coinmarketcap. Bitcoin is the dominant cryptocurrency with 51,9% of the total market capitalization on April 12, 2019 (Coinmarketcap 2019a).

The existing literature in this field mainly focuses on Bitcoin, since it is the largest cryptocurrency, which means that the research regarding other important cryptocurrencies is limited. Previous research has studied the inefficiency (Urquhart 2016; Nadarajah and Chu 2017; Cheah et al. 2018) and volatility of Bitcoin (Dwyer 2015; Dyhrberg 2016). Only a few studies have focused on the long-run relationship between cryptocurrencies, even though they are highly correlated (Leung and Nguyen 2018). The purpose of this paper is to bridge that gap by analyzing the top six cryptocurrencies by market capitalization; Bitcoin, Ethereum, Ripple (XRP), Bitcoin Cash, Litecoin and EOS.

The objective of this study is to analyze if there exists a long-run relationship between the price of Bitcoin and five observed cryptocurrencies by testing for cointegration. In this study the Johansen cointegration test and the Engle-Granger two step analysis for cointegration are conducted to evaluate if there are any cointegrating pairs between Bitcoin and the five altcoins. A Vector Error Correction Model (VECM) is conducted in order to estimate a potential long-run relationship. Cointegration is an area that is relatively unexplored when it comes to cryptocurrencies, which makes it interesting to analyze. Leung and Nguyen (2018) state that the high correlation among cryptocurrencies is a reason to investigate cointegration. They analyze cointegration in the cryptocurrency market by conducting both the Johansen test and the Engle-Granger two step method. Ciaian, Rajcaniova and Kancs (2018) applies the Autoregressive Distributed Lag (ARDL) model to investigate if there is cointegration between cryptocurrencies. The findings from these studies are discussed in more detail in section two.

Given the arguments presented above, this study will primarily focus on the following question:

- Are there any cointegrated pairs among Bitcoin and Bitcoin Cash, EOS, Ethereum, Litecoin and Ripple?

This is potentially important because by answering this question, it will be possible for investors to determine how to act on the cryptocurrency market. If Bitcoin is cointegrated with any of the other cryptocurrencies, it implies that there is a long-run relationship between them. This can be used by investors to make strategic trading decisions. For example, pairs trading is a statistical arbitrage strategy based on cointegration and can be used to forecast prices of cryptocurrencies (Stübinger 2019). The investment strategy seeks to identify two assets that have similar price movements and can be used by traders if the assets are cointegrated. When there is a deviation from the long-run equilibrium, the investors can act on that in the belief that it will return to the long-run equilibrium.

This study contributes to the existing literature on the financial aspect of the cryptocurrency market. Investigating cointegration among cryptocurrencies will provide information about the price formation of cryptocurrencies. The results from the Engle-Granger test and the Johansen tests for cointegration show that Bitcoin is cointegrated with Bitcoin Cash, Ethereum, Litecoin, and Ripple. On the other hand, both tests suggest that Bitcoin and EOS do not have a cointegrating relationship. The results from VECM estimation imply that the Bitcoin price has a statistically significant long-run effect on the prices of Bitcoin Cash, Ethereum, Litecoin and Ripple.

The remainder of this paper is structured as follows. Section two provides a literature review, with a focus on cointegration for assets and previous studies on cryptocurrencies. In section three, the methodology that is used for the study is explained. Section four presents the data and describes the main features of the six cryptocurrencies that are included in this study. Section five presents the results from the cointegration tests and the VECM, while section six concludes the paper.

2. Literature review

In this section the literature regarding cointegration will first be presented. Then the literature about cryptocurrencies will be reviewed. The literature about cointegration analysis was selected with the purpose of providing an understanding of the concept of cointegration. Since the literature about cryptocurrencies is limited, the previous research that was included in the literature review were studies that related to the topic of cointegration among cryptocurrencies.

Since the concept of cointegration was introduced by Engle and Granger in 1987, many economists have applied that residual-based method to analyze non-stationary time series. Johansen (1988) suggested a new approach to test for cointegration, which made it possible to test for multiple cointegrating relationships. Stock and Watson (1988) stated that cointegrated multiple variables share at least one common trend and developed a common trend test for multivariate time series. Phillips and Ouliaris (1990) proposed a residual based cointegration test that provided different critical values than Engle and Granger (1987). Gregory and Hansen (1996) also developed a residual based cointegration test which allows for the possibility of regime shifts and where the data has structural breaks. The majority of previous studies regarding cointegration are either related to the stock market (Kasa 1992; Lettau and Ludvigson 2001; Chen, Firth and Meng Rui 2002; Bessler and Yang 2003) or to energy economics (Soytas and Sari 2003; Ang 2007; Acaravci et al. 2012).

There are only a few studies that have been published about cointegration among cryptocurrencies. Most previous research related to the financial aspects of cryptocurrencies have been focusing on efficiency (Urquart 2016; Cheah et.al 2018), volatility (Baek and Elbeck 2015) and price formation (Ciaian, Rajcaniova and Kancs 2016). The following studies are the available previous studies, that are most similar to this research.

Bação et al. (2018) analyzed the information transmissions between the prices of Bitcoin, Ethereum, Ripple, Litecoin and Bitcoin Cash. They assumed that the price between cryptocurrencies should be closely related in both the long- and short-run. They concluded that the cryptocurrencies were indeed closely related, and that the majority of information transmissions took place within a day. It was also concluded that Litecoin was the information transmission leader of the five cryptocurrencies that were part of the study.

Jaureguizar et al. (2018) examined the correlation between 16 different cryptocurrencies between July 2017 and February 2018. By using daily price data and Pearson correlations, Jaureguizar et al. identified Ethereum as a benchmark currency that acted as connector between cryptocurrencies, even though Bitcoin is the most popular cryptocurrency. They argued that it might be the case that Bitcoin is only regarded a medium of exchange, whereas Ethereum is more versatile project that can be used to create decentralized applications. According to Jaureguizar et al., this could explain why Bitcoin does not appear to be the central cryptocurrency in the study. The aim of the study was to provide knowledge of the cryptocurrency market to help investors understand what mechanisms influence the price formation of cryptocurrencies.

Sovbetov (2018) studied factors that affect the price of Bitcoin, Ethereum, Dash, Litecoin and Monero by using weakly data from 2010 to 2018. In the study, the ARDL method was used in order to investigate how the prices of the cryptocurrencies were affected in both the short- and long-run. Sovbetov found that factors such that trading volume and volatility had an impact on the price for all five cryptocurrencies, in the short-run as well as the in the long-run. The results implied that the stock market index S&P 500 had a weakly positive influence on Bitcoin, Ethereum and Litecoin in the long-run, but these relationships seemed to disappear in the short-run. The study also provided error-correction models for the five cryptocurrencies, which showed that cointegrated series did not drift too far apart.

Ciaian, Rajcaniova and Kancs (2018) stated three main reasons to believe that the Bitcoin and altcoin markets might be highly interdependent. To begin with, Bitcoin is the dominant cryptocurrency. Furthermore, the price developments in the prices of altcoins are similar to the changes in the price of Bitcoin. In addition, Bitcoin is often used as a medium of exchange when purchasing altcoins. Ciaian, Rajcaniova and Kancs (2018) studied the relationship between Bitcoin and altcoin prices in the short- and the long-run. The aim was to investigate if Bitcoin drove the price of altcoins. They examined if Bitcoin and the altcoins were cointegrated by analyzing daily data of 17 different cryptocurrencies for the period 2013-2016 and performing an ARDL-test. Their findings suggested the interdependency between the price of Bitcoin and the price of altcoins was stronger in the short-run than in the long-run. They found that the price of Bitcoin had an impact on the prices of 15 altcoins in the short-run, but only 4 altcoins had a long-run cointegrating relationship with Bitcoin.

Leung and Nguyen (2018) analyzed the process of constructing cointegrated portfolios of the cryptocurrencies Bitcoin, Ethereum, Litecoin and Bitcoin Cash, by conducting both the Johansen cointegration test and the Engle-Granger two-step procedure. Their study includes price data for the four cryptocurrencies, which was gathered from December 20, 2017 to June 20, 2018. In their study they concluded that the observed cryptocurrencies were I(1) processes. Leung and Nguyen found that price cointegration existed among the four cryptocurrencies. The aim of the study was to construct a tradeable mean-reverting portfolio, which was the reason for testing for cointegration. After it was clear that there was a cointegrating relationship between the observed cryptocurrencies, they performed three different unit-root tests on the residuals to establish stationarity. The findings from all three tests implied that the residuals were stationary, which confirmed that they were cointegrated. Leung and Nguyen argued that it is not only important to investors, but also to regulators, to understand the cryptocurrency market and the interdependency between cryptocurrencies.

Van den Broek[1] (2018) examined if there were cointegrating pairs in the cryptocurrency market. The purpose of the study was to investigate the possibility of pairs trading in the cryptocurrency market, which is a trading strategy that takes advantage of price differences to make a profit. The dataset included 34 cryptocurrencies that were observed in the time period September, 15 2017 to April, 15 2018. In this research, the Engle-Granger method was applied to find cointegrating pairs. Van den Broek found that 31 pairs exhibited a cointegrating relationship.

This study is closely related to the work of Ciaian, Rajcaniova and Kancs (2018), Leung and Nguyen (2018) and Van den Broek (2018). Both the Johansen approach and the Engle-Granger method are applied to six of the most popular cryptocurrencies, which makes the study similar to the work of Leung and Nguyen. This thesis investigates cointegrating pairs, analogous to the study by Van den Broek. The main difference with this research compared to Leung and Nguyen (2018) and Van den Broek (2018), is that they construct possible trading strategies, while this study aims to investigate cointegration.

[1] This is a thesis and has thus not been peer reviewed.

3. Methodology

In this section the methodology used in this study is explained. First, the concept of cointegration is explained. Then the Dickey-Fuller test for unit root is defined, as well as the Engle-Granger method and Johansen's cointegration method.

3.1 Cointegration

Stock and Watson (2015) defines cointegration as "when two or more time series variables share a common stochastic trend". Cointegration was first introduced by Granger (1981) and later studied by Engle and Granger (1987). Engle and Granger developed a method that can be used to analyze time series data with common trends that is based on regression. They showed that even though correlation between two non-stationary time series can be significant, this does not necessarily indicate that there is an important connection between them. If statistical methods for stationary data are applied on non-stationary time series, this can result in meaningless relationships that are called spurious.

Murray (1994) illustrated cointegration and error correction by a humorous example of a drunk and her dog. The drunk person and her dog come out from a bar. Both wander aimlessly in the night. Individually, the walk of the drunk illustrates a random walk, as well as the path of her unleashed dog. From time to time, the drunk owner will call for her dog if it wanders too far away. When the owner calls, the dog will interrupt his aimless wandering and catch up with the owner. The distance between the drunk and the dog will therefore be relatively stable. This suggests that the drunk woman will follow a non-stationary process, as well as her dog. But the long-run relationship between them will be stationary.

A time series is non-stationary and contains a unit root if it is integrated of order 1, which is called an I(1) process. Financial variables are most often non-stationary. When two or more non-stationary time series move together over time and thus share a common stochastic trend, they are said to be cointegrated. Cointegrating variables have a long-run relationship and can deviate from this connection in the short-run, but return to the long-run equilibrium (Brooks 2008).

This study examines if there is cointegration between Bitcoin and five altcoins. Let Y_t denote the Bitcoin price and X_t the price of the altcoin. If Y_t and X_t are both I(1) processes, they are said to be cointegrated if there exists some stationary, I(0), linear combination between them.

3.2 Unit Root Testing

To begin with, the data needs to be tested to ensure that the time series is non-stationary. This can be made by using a unit root test. In this study, both the Dickey-Fuller test and the augmented Dickey-Fuller test will be performed to validate if the variables are non-stationary and follow a unit-root process (Dickey and Fuller 1979). Each time series will be tested individually for a unit root.

The Dickey-Fuller test is the easiest way to test for a unit root. The equation of the Dickey-Fuller test looks as follows:

$$\Delta y_t = \alpha y_{t-1} + u_t \tag{1}$$

where u_t is a white noise variable. The Dickey-Fuller test tests the null-hypothesis of a unit root in the data, $\alpha = 0$. The alternative hypothesis is that $\alpha < 0$ and that there is no unit root, which means that the data is stationary. If the test statistic is more negative than the critical value, the null-hypothesis will be rejected in favor of the alternative.

The augmented Dickey-Fuller test adds lags to the model and also test for a unit root in the time series data. The purpose of including lags is to eliminate autocorrelation of the random term u_t and the dependent variable. The number of lags can be estimated using the Schwarz's Bayesian information criterion (SBIC) or the Akaike information criterion (AIC). Brooks (2008) state that both criterions have advantages and disadvantages and that no criterion is overall preferred. According to Brooks (2008), AIC is usually efficient but not consistent, while SBIC is consistent but inefficient. The number of lags will be selected according to the AIC, which is often used in practice (Stock and Watson 2015). The regression that is tested in the augmented Dickey-Fuller test follows from the equation:

$$\Delta y_t = \alpha y_{t-1} + \sum_{i=1}^{\rho} \gamma_i \Delta y_{t-i} + u_t \tag{2}$$

where ρ is the number of lags of the dependent variable.

The ADF-test tests the same hypotheses as the standard Dickey-Fuller test, which means that y_t has a stochastic trend and is non-stationary under the null-hypothesis and under the alternative-hypothesis, y_t is stationary (Brooks 2008).

3.3 Johansen's Cointegration Method

There are different approaches to testing for cointegration. Johansen (1988, 1991) introduced a test based on maximum likelihood to analyze if multiple time series form cointegrating relationships. In this study, the Johansen-test will first be performed, followed by the Engle-Granger test. There are two types of Johansen test, which are called the maximum eigenvalue test and the trace test.

Johansen's method is based on vector autoregression (VAR), which is a model that is used to capture linear relationships of multiple time series. In order to compute Johansen's cointegration test, the VAR has to be turned into a vector error correction model (VECM) by adding error correction components (Brooks 2008). The estimation model takes the form:

$$\Delta y_{t=}\Pi y_{t-k} + \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \cdots + \Gamma_{k-1} \Delta y_{t-(k-1)} + u_t \qquad (3)$$

where k is the number of lags, $\Pi = \left(\sum_{i=1}^{k} \beta_i\right) - I_g$ and $\Gamma = \left(\sum_{j=1}^{k} \beta_j\right) - I_g$, which are two matrices. The matrix Γ catches the short-run dynamics, while the matrix Π contains the long-run effects. There is a set of g variables in the model which is equal or larger than two. The Johansen test focuses on the matrix Π. Each rank, r, of the matrix Π, is tested where the rank of the matrix equals the number of its eigenvalues that are different from zero. The Johansen test consists of two test statistics that will be used in this research. The trace statistic, which is a joint test that tests the null-hypothesis that the number of cointegrating vectors is equal to zero and that there is no cointegration against the alternative-hypothesis that there is cointegration. The max statistic conducts tests on each eigenvalue and can also be tested. The null-hypothesis is that r is the number of cointegrating vectors and tests the null against the alternative-hypothesis that the number of cointegrating vectors is $r + 1$. The trace statistic is formulated as:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_i) \tag{4}$$

and the max statistic follows by

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \tag{5}$$

where r is the number of cointegrating vectors under the null-hypothesis and $\hat{\lambda}_i$ is the estimated ith ordered eigenvalue from the matrix (Brooks 2008).

If the trace statistic is larger than the critical value, the null-hypothesis is rejected to the advantage to the alternative-hypothesis. If the null-hypothesis is not rejected in the first test, it concludes that there is no cointegration among the variables. If the null-hypothesis is rejected, then the test continues where the new null-hypothesis is that $r = 1$ is tested against the alternative that the cointegrating vectors are $r + 1$. The value of r is increased until the null-hypothesis cannot be rejected any longer. The matrix can have a maximum of $g - 1$ ranks, which means that if two variables are tested, it can have a maximum rank of 1 if there is cointegration. If instead three variables are included in the Johansen test, it can have a maximum rank of 2. If the matrix is of full rank it would imply that the data is stationary (Brooks 2008).

In order to determine the deterministic components, a method called the *Pantula principle* was relied on. This method, which was stated in Pantula (1989), has for example been applied by Johansen (1992). According to the Pantula principle, the first model that is tested should be the most restricted model with no deterministic components. If the model is rejected, the next step is to test a model with a restricted constant. The process continues by moving from the most restrictive model to the least restrictive model. At every step, the test statistic is compared to the critical value. When it is no longer possible to reject the null hypothesis for the first time, the process ends.

The Johansen test has some statistical disadvantages when the sample size is less than 50 observations (Mishra, Nielsen and Smyth 2010). Since the sample size is large in this study, there is no need for concern on that note. After the Johansen test is performed, the Engle-Granger test will be conducted.

3.4 Engle-Granger Method

The most well-known method to test for cointegration was formed by Engle and Granger (1987). In the Engle-Granger 2-step procedure, the first step is to run an OLS regression on the equation:

$$Y_t = \beta_1 + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_k X_{kt} + u_t \quad (6)$$

where u_t are the residuals and there are k variables. Since pairs are tested in this paper, there is only Y_t and X_t and the equation will thereby follow from:

$$Y_t = \beta_1 + \beta_2 X_t + u_t \quad (7)$$

If the residuals are stationary, this is a sign of a cointegrating relationship among the variables. If the residuals are non-stationary, this implies that the variables are not cointegrated. To test if the residuals are stationary, we conduct the augmented Dickey-Fuller test (ADF-test) and the standard Dickey-Fuller test (DF-test) on the residuals. The regression that is used on the residuals is:

$$\Delta\hat{u}_t = \psi\hat{u}_{t-1} + v_t \quad (8)$$

In the Engle-Granger cointegration test, specific critical values are used, which come from Engle and Yoo (1987). The reason why the critical values are different from the unit-root testing with data is that this is a test for the residuals. These critical values are larger in absolute value than the standard Dickey-Fuller critical values (Brooks 2008). In this case there are over 200 observations and the number of variables is two. Table 1 displays the critical values for the Engle-Granger test (Engle and Yoo 1987).

Table 1. Critical values for Engle-Granger test

Significance Level	Critical Values
1%	-4,0
5%	-3,37
10%	-3,02

The tested hypothesis for the unit root test for the residuals is:

H_0: The residuals are non-stationary, $\hat{u}_t \sim I(1)$
H_A: The residuals are stationary, $\hat{u}_t \sim I(0)$

Under the null-hypothesis, the residuals are non-stationary, which means that the variables Y_t and X_t are not cointegrated. Should the null-hypothesis be rejected in favor of the alternative, it implies that the residuals are stationary and that there is a cointegrating relationship between Y_t and X_t (Brooks 2008).

When two variables are tested for cointegration it is only possible that one linear combination of the variables exists. The Engle-Granger approach can be used when testing for one cointegrating relationship. If more than two variables are analyzed, Johansen's method is the recommended test, since Johansen's test can be used to test multiple cointegrating relationships. Since the analysis for this research is pair-wise, it is both possible to perform the Engle-Granger test and Johansen's method to test for cointegration.

3.5 VECM

If the variables are found to have a cointegrating vector in the cointegration tests, then the Vector Error Correction Model (VECM) can be used to make estimations of the cointegrating vectors. A formal description of a VECM can be found in equation 3. The Johansen cointegration test, which is stated in section 3.3, examines the matrix Π. It can be explained as a long-run coefficient matrix and is defined as the product of two matrices

$$\Pi = \alpha\beta' \qquad (9)$$

where the matrix β provides the cointegrating vectors and the matrix α gives the adjustment parameters (Brooks 2008). The adjustment parameter measures the speed at which deviations from the equilibrium adjust toward the long-run equilibrium, while β contains the long-run relationship among the variables. A statistically significant coefficient β suggests that a long-run relationship between the altcoin price and the Bitcoin price exists. Ciaian, Rajcaniova and Kancs (2018) state that a series with statistically significant short-run as well as long-run coefficients, implies that there is a strong causal effect on the dependent variable.

4. Data

In order to test if there are cointegrated pairs in the cryptocurrency market, historical price data is required. The data that was used in this study is the daily closing price data of five cryptocurrencies, which was retrieved from Coinmarketcap, a website that provides information on various cryptocurrencies. The data was collected from five different time periods, all ending on April 9, 2019. The motive behind the five different sample periods was to provide as large samples as possible for each cryptocurrency. The longest time series contained over 2100 observations and the shortest about 620 observations. The statistical program which was used to perform the tests was Stata. The cryptocurrencies that this study will examine are Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Bitcoin Cash (BCH) and EOS. Since these cryptocurrencies were established at different times, with Bitcoin being the oldest cryptocurrency, the pairs are observed at different time periods.

Table 2. Cryptocurrencies selected for the study and their price, market capitalization and volume in USD on May 9, 2019.

Name	Code	Price	Market Cap	Volume (24h)
Bitcoin	BTC	$6069,47	$107 374 061 748	$15 978 907 214
Ethereum	ETH	$170,17	$18 036 757 244	$6 576 231 785
Ripple	XRP	$0,299099	$12 602 021 325	$883 638 871
Bitcoin Cash	BCH	$284,66	$5 059 097 234	$1 276 115 424
Litecoin	LTC	$73,76	$4 550 471 831	$2 613 860 144
EOS	EOS	$4,87	$4 436 429 395	$1 617 245 273

Source: Coinmarketcap.com

4.1 Description of the observed cryptocurrencies

The following sections describe the cryptocurrencies that are examined in this study, which are Bitcoin, Ethereum, Ripple (XRP), Bitcoin Cash, EOS and Litecoin.

4.1.1 Bitcoin

Bitcoin was the first decentralized digital currency and was created in 2008 by an anonymous person or a group called Satoshi Nakamoto. Bitcoin is a peer-to-peer electronic cash system which only exists in digital form. Decentralized means that no single individual or firm can control the network. Bitcoin is also open source, which means that anyone can view the code. The initial purpose of Bitcoin was to allow online payments to be sent directly from one person to another, without involving a financial institution. Instead of a trusted third party, Bitcoin uses cryptographic proof to validate transactions, which is the reason why Bitcoin is called a cryptocurrency.

Since there is no central authority that verifies the transactions, Bitcoin uses a technology that is called blockchain. The blockchain is an immutable distributed ledger, which is public and available to everyone. Every transaction that occurs in the network is saved in the blockchain and can be viewed by everyone. Users of the network maintain the network functioning by providing CPU power from their computers. These users are called miners and they validate transactions by collecting new transactions into blocks. Miners compete against each other to create blocks, by finding a proof-of-work for the block. When a miner finds a proof-of-work, it will broadcast this to the network. The network provides incentives to users to become miners, which comes in the form of new bitcoins and transaction fees (Nakamoto, 2008). The supply of Bitcoin is fixed at 21 million and the circulating supply is currently 17,6 million (Coinmarketcap 2019a).

4.1.2 Ethereum

Ethereum is a decentralized network that was founded in 2013 by the programmer Vitalik Buterin. The network is called Ethereum and the actual cryptocurrency is named Ether, but Ethereum is commonly used to refer to both the network and the cryptocurrency (Coinmarketcap 2019b). Ethereum is based on blockchain technology and was the first that launched blockchain based smart contracts. Smart contracts are pieces of code that digitally store, verify and self-execute rules. Smart contracts don’t need an intermediary. Ethereum enables developers to build decentralized applications, which are called dapps, on the blockchain. The programming language Solidity is the primary language for the Ethereum platform (Ethereum 2019a). Miners are the ones that keep the platform secure and running. Every 15 seconds a new block is created and added to the Ethereum blockchain. The miners that generate new blocks are awarded 3 ether for each new block (Ethereum 2019b).

4.1.3 Ripple (XRP)

Ripple is a network, a company and a cryptocurrency. The actual cryptocurrency that is used by the Ripple network is called XRP. The company Ripple was founded 2012 in San Francisco and uses the Ripple network to make global payments faster and less costly (Bajpai 2019). Ripple offers an alternative to SWIFT and works with financial institutions like Santander and American Express. When a transaction occurs, fiat money is converted to XRP and can be transacted through the Ripple network and can then be converted back to traditional money.

When constructing XRP, the goal was to construct a fast and cost-efficient cryptocurrency. Payments settle in four seconds and XRP handles 1500 transactions per second (Ripple 2019). XRP has been criticized for being centralized, since the company Ripple owns 60% of XRP (Löfström and Ploog 2018).

The main difference between XRP and Bitcoin is that XRP is not mined. There is a maximum supply of 100 billion XRP tokens which are pre-mined. As of April 2019, there are 42 billion XRP in the market according to Coinmarketcap and the rest of the supply is locked into a series of escrows. New XRP is brought into circulation periodically (Schwartz 2017). Ripple does not have a blockchain. Instead it uses the Ripple Protocol Consensus Algorithm (RPCA), a technology designed by Ripple itself (Cointelegraph).

4.1.4 Bitcoin Cash

Bitcoin Cash is an updated version and a hard fork of Bitcoin. A hard fork is a change to the protocol, which basically means that the blockchain and the cryptocurrency was split in two. Bitcoin Cash shared the same transaction history as Bitcoin until the hard fork took place on August 1st. After the hard fork, both Bitcoin and Bitcoin Cash have separate transaction history and are two different cryptocurrencies. The main difference between Bitcoin and Bitcoin Cash is the block size. When the hard fork took place, Bitcoin had a 1 MB block size whereas Bitcoin Cash had an 8 MB block size. This means that Bitcoin Cash has more transactions per block than Bitcoin (Bajpai 2019). Transactions can take place faster, but more blocks also mean that there is more data to process. As of today, Bitcoin Cash has a block size of 32 MB (bitcoin.com). In November 2018, there was another hard fork that split Bitcoin Cash in two. Bitcoin ABC was the name of the dominant chain (Coinmarketcap 2019d).

4.1.5 EOS

EOS is a rather new cryptocurrency that was developed in 2017. It was first launched as an initial coin offering (ICO), which is a way of collecting funds for a project and is similar to an IPO. The ICO raised about four billion dollars and the platform was released as open source in June 2018. EOS has some similarities to Ethereum, since it also is a decentralized network which operates smart contracts. Like Ethereum, EOS is constructed to support decentralized applications on the blockchain. The objective of EOS is to eliminate transaction costs and to enable millions of transactions per second to be conducted (Bajpai 2019). EOS uses delegated proof of stake instead of proof of work. In the case of EOS, 21 block producers are selected by a vote from token holders. These block producers validate transactions and add them on the blockchain. Block producers are rewarded when they have produced a new block (Löfström and Ploog 2018).

4.1.6 Litecoin

Litecoin was created in 2011 by Charlie Lee. The idea behind Litecoin was to create a cryptocurrency which could process payments faster than Bitcoin. With Litecoin it takes 2,5 minutes to generate a new block, compared to the 10-minute confirmation time that Bitcoin has (Coindesk 2019). Litecoin and Bitcoin are technologically very much alike, but Litecoin uses another hashing algorithm than Bitcoin, called Scrypt. Litecoin miners are awarded with 25 new coins per block. Approximately every four years this amount gets halved. The network is designed to produce 84 million coins. Some updates, like lightening network, have first been implemented in Litecoin and later used by Bitcoin. Lightening network basically means that smaller transactions can be handled outside of the blockchain. This will make payments faster and transaction fees low (Litecoin 2019).

4.2 Descriptive statistics

Table 3. Descriptive statistics

	Bitcoin	Ethereum	XRP	Bitcoin Cash	EOS	Litecoin

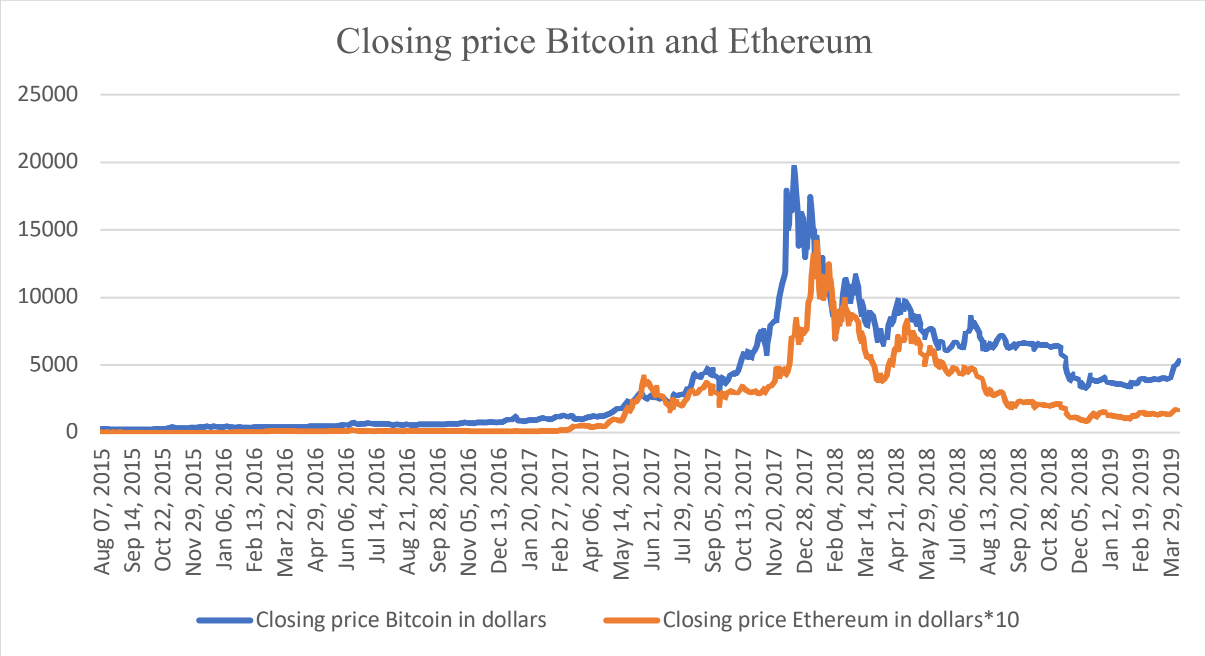
Maximum price	19497.4	1396.42	3.38	3923.07	21.54	358.34
Minimum price	68.43	.43	.0028	77.37	.4932	1.16
Mean price	2382.2	205.07	.1738	759.24	5.611	31.87
Std.Dev	3355.39	265.41	.3343	631.11	4.161	52.78
Number of Obs	2,173	1,342	2,075	626	648	2,173

The table presents descriptive data of the cryptocurrencies that are observed in this study in USD. Note that the cryptocurrencies are observed in different time periods, which is the reason for the difference in the number of observations. Litecoin has the longest time series of the five altcoins and therefor the descriptive data for Bitcoin is also examined with the same number of observations as Litecoin. There shortest time series belongs to Bitcoin Cash, with 626 observations. As can be seen in the table, the cryptocurrencies have fluctuating prices. The differences between the maximum and the minimum prices are large. Bitcoin had a maximum price of almost 20 000 dollars and a minimum price of 68 dollars during the sample period. The highest price of Ethereum was about 1400 dollars, whereas the mean price was a bit over 200 dollars. There are also large price differences between the cryptocurrencies. For example, the mean price of XRP was 0.17 dollars, while the average price of Bitcoin was 2382 dollars. For a more extensive overview of the descriptive statistics in the different time periods, this can be found in the appendix.

4.3 Graphical representation of prices over time

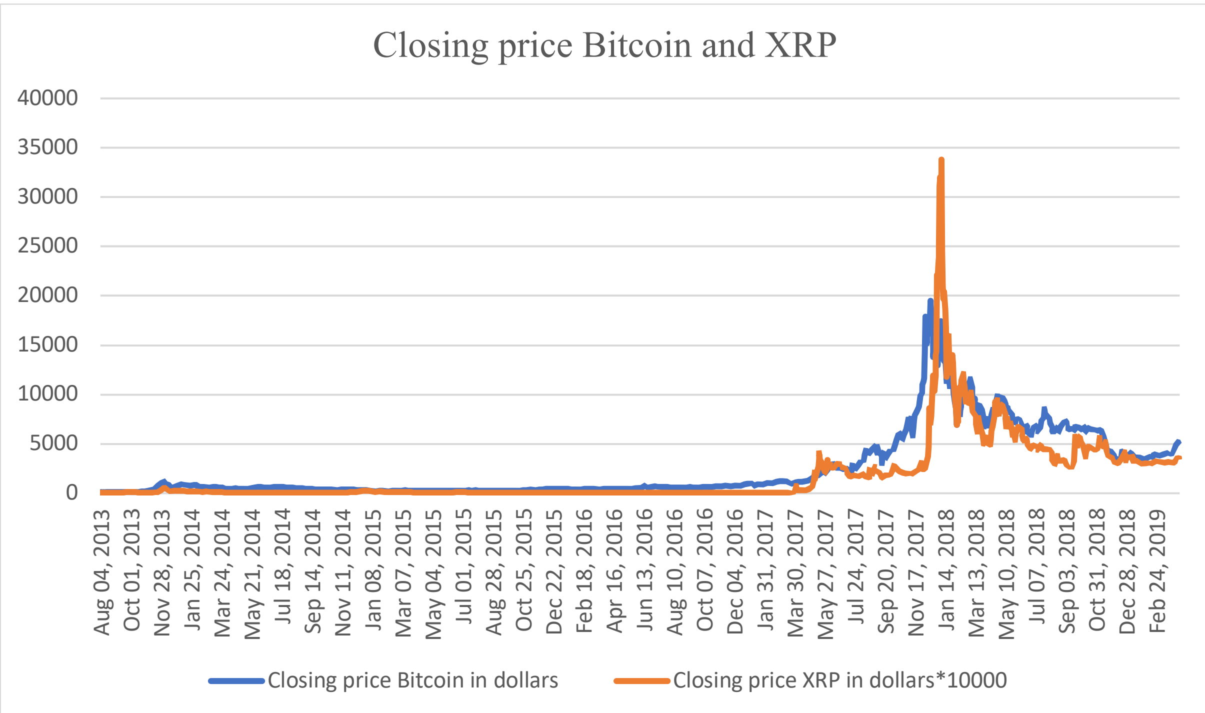
The price data for Bitcoin has been graphed with the five other cryptocurrencies in the time periods that were tested for cointegration.

Figure 1. Closing price for Bitcoin and Ethereum



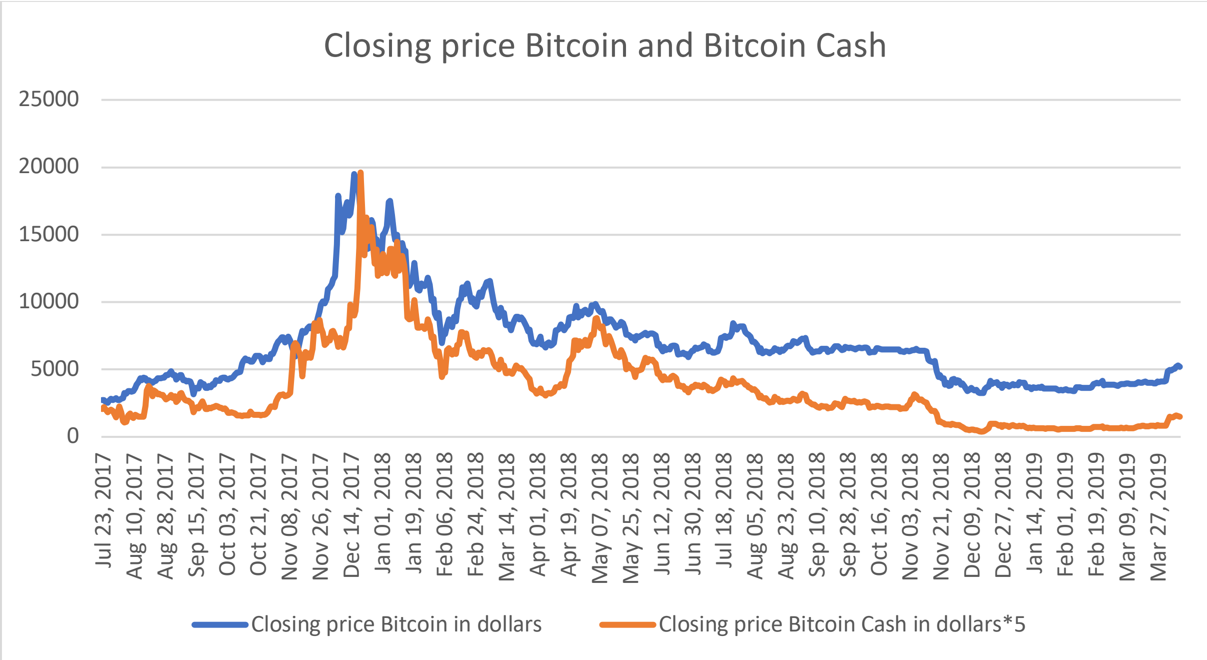
Closing price in USD for Bitcoin and Ethereum from August 7 2015 to April 9 2019. The closing price for Ethereum has been multiplied by 10 in order to observe price changes graphically.

Figure 2. Closing price for Bitcoin and XRP



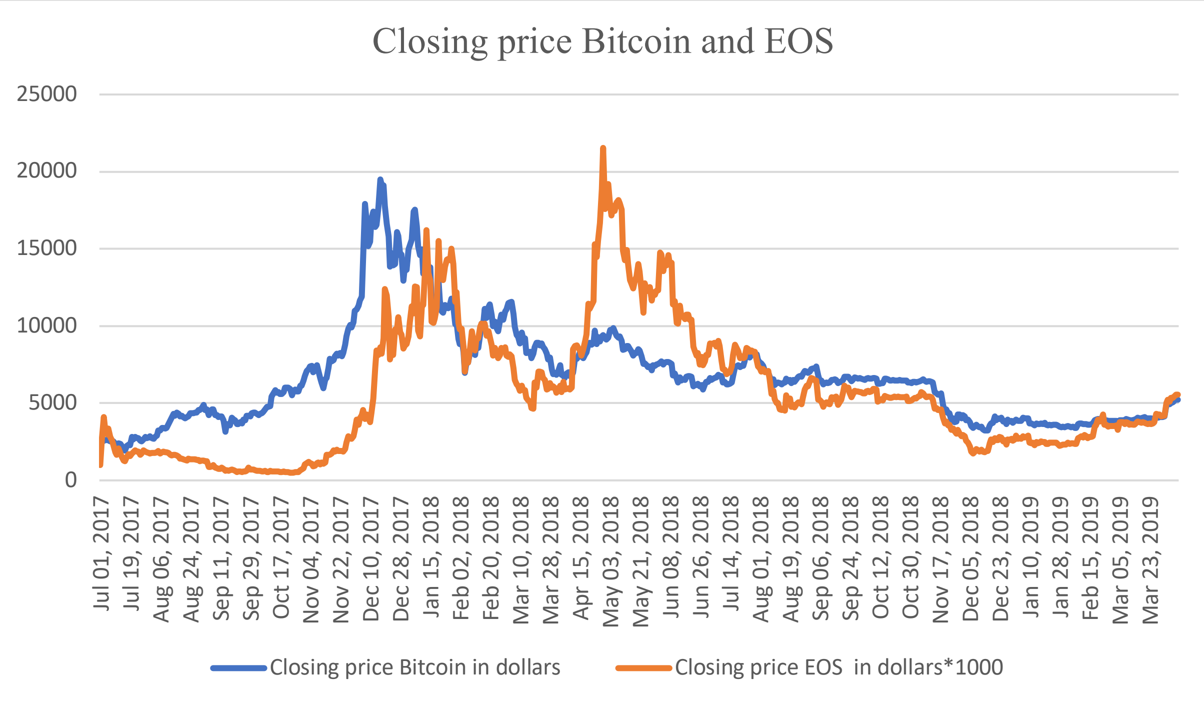
Closing price for Bitcoin and XRP from August 4 2013 to April 9 2019 in USD. The XRP-price has been multiplied by 10 000 in order to visually observe the changes in price.

Figure 3. Closing price for Bitcoin and Bitcoin Cash



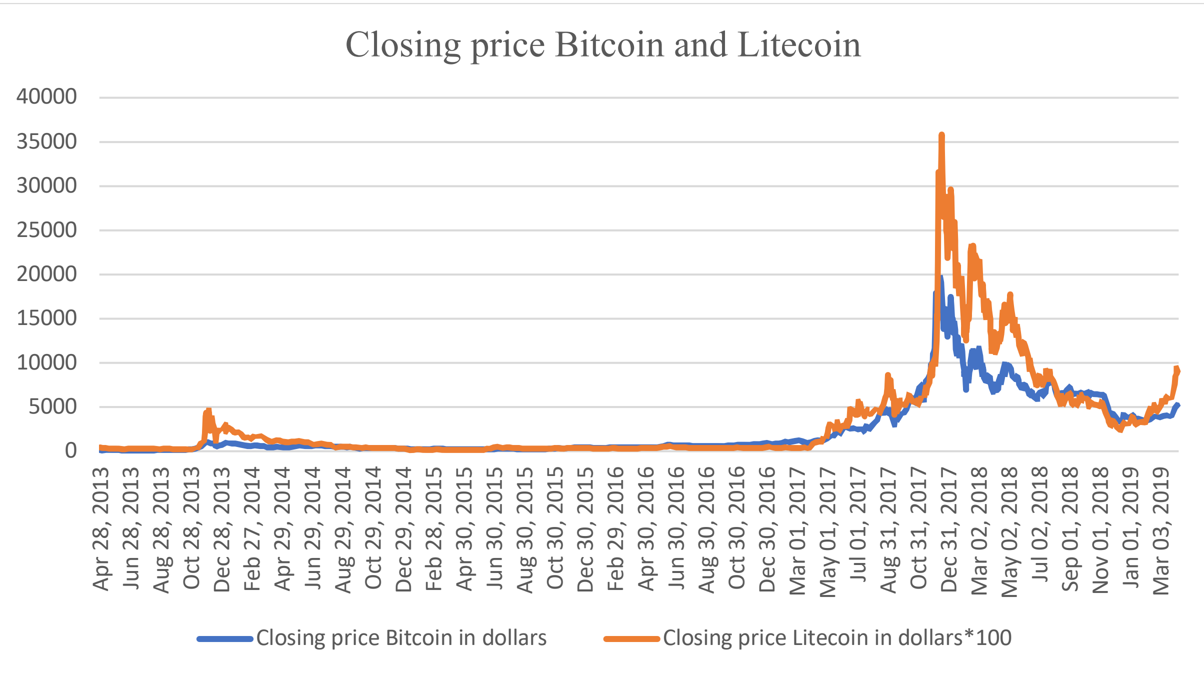
Closing price for Bitcoin and Bitcoin Cash in USD from July 23 2017 to April 9 2019. The price of Bitcoin Cash has been scaled up by 5 in the graph.

Figure 4. Closing price for Bitcoin and EOS



Closing price data for Bitcoin and EOS in USD from June 1 2017 to April 9 2019. The closing price for EOS has been multiplied by 1000 in order to observe the price changes visually.

Figure 5. Closing price for Bitcoin and Litecoin



The closing prices for Bitcoin and Litecoin in USD, where the price of Litecoin is multiplied by 100. The data starts April 28, 2013 and ends April 9, 2019.

It is only possible to observe the larger movements in price in these figures. By observing the figures, it seems like the prices have moved in the same direction in most cases during the sample period. The similar price movements could imply that there might be a cointegrating relationship between Bitcoin and some of the altcoins. In the end of 2017, it appears that all of the cryptocurrencies might have experienced a bubble, with a rapid increase in price followed by a price reduction in the beginning of 2018. The majority of the cryptocurrencies had a peak in the price in December 2017, with EOS being the exception. The price of EOS was higher in May 2018 than in December 2017. This might indicate that something other than the price of Bitcoin had an impact on the price of EOS. Bitcoin and EOS do not appear to have a strong long-run relationship, while the other cryptocurrencies seem to be cointegrated with Bitcoin.

5. Results

First of all, it was tested if the data was non stationary, by performing the augmented Dickey-Fuller test. The standard Dickey-Fuller test and a Phillips-Perron unit root test were also executed as complements to the ADF-test. The augmented Dickey-Fuller test was implemented with no constant and no trend, but with lags. The lags were chosen after checking the lag-order selection statistics. The Akaike information criterion (AIC) was used to estimate the number of lags for the tests. The result from this test can be found in the appendix. The result from the augmented Dickey-Fuller test showed that it was not possible to reject the null hypothesis that the variables Bitcoin, Bitcoin Cash, EOS, Ethereum and Litecoin exhibited a unit root, which meant that the data was non stationary. The Dickey-Fuller test and the Phillips-Perron test yielded the same conclusions.

There was one time series that did not show clear signs of non-stationarity, which was XRP. In the augmented Dickey-Fuller test with four lags, it was not possible to reject the null-hypothesis of a unit root for XRP. If the lag length would have been determined by SBIC instead of AIC, two lags would have been used. The augmented Dickey-Fuller test was therefor also performed with two lags, to test if it would yield the same result as the test with four lags. It was possible to accept the null-hypothesis of a unit root at 1% critical value, but at a significance level of 5%, the null-hypothesis of a unit root was rejected. The standard Dickey-Fuller test gave the same result as the augmented Dickey-Fuller test with two lags and the Phillips-Perron test showed similar results. The variable was further tested for a unit root and the sample period was divided into two periods. The result from the stationarity tests for both subperiods, implied that the variable XRP was non-stationary during both time periods. The cointegration-analysis will include XRP, even if it is not clear whether or not the data is non-stationary, since the results are ambiguous. The graphed closing price data for the variable in figure 2 does not indicate that the data could be stationary and because the time series for XRP is similar to the time series of other cryptocurrencies, there is a reason to include the variable. The results from the stationarity tests can be found in the appendix.

After checking if the data was non-stationary, a Johansen cointegration test was performed. By observing the lag-order statistics, the variables were lagged in the Johansen test according to the AIC. The test result from the lag-order statistics are available in the appendix. Following

Pantulas principle, the Johansen test was first performed without a trend and with lags. When including a constant trend, this gave results that were not possible to interpret, since the null hypothesis was rejected at every rank. This provided evidence that the model should not include any deterministic trend variables. In the Johansen test, we look at the trace statistic and observe if it is smaller or larger than the critical value. If the trace statistic is larger than the critical value, we reject the null-hypothesis. From the result from the Johansen cointegration test we could reject the null-hypothesis that there was zero cointegrating relationship in four out of five cases. The null of one cointegrating relationship was accepted in all of these cases. This concludes that a cointegrating relationship exists between Bitcoin and the altcoins Bitcoin Cash, Ethereum, Litecoin, and XRP in the tested time period. From the test result it was concluded that Bitcoin and EOS were not cointegrated, since the null-hypothesis of zero cointegration was accepted. The test results from Johansen's cointegration test are found in tables four to nine.

Table 4. Johansen tests for cointegration between Bitcoin and Bitcoin Cash

Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
0	12	-8342.0202		20.1529	12.53
1	15	-8332.1542	0.03123	0.4208*	3.84
2	16	-8331.9438	0.00068		

Maximum rank	Parms	LL	Eigenvalue	Max statistic	5% critical value
0	12	-8342.0202		19.7321	11.44
1	15	-8332.1542	0.03123	0.4208*	3.84
2	16	-8331.9438	0.00068	0.4208	

Bitcoin and Bitcoin Cash	Number of obs: 622
Sample: 5-626	Lags: 4
Trend: none	

Table 5. Johansen tests for cointegration between Bitcoin and Ethereum

Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
0	12	-15202.815		28.5239	12.53
1	15	-15189.555	0.01963	2.0043*	3.84
2	16	-15188.553	0.00150		

Maximum rank	Parms	LL	Eigenvalue	Max statistic	5% critical value
0	12	-15202.815		26.5196	11.44
1	15	-15189.555	0.01963	2.0043*	3.84
2	16	-15188.553	0.00150		

Bitcoin and Ethereum Number of obs: 1338

Sample: 5-1342 Lags: 4

Trend: none

Table 6. Johansen tests for cointegration between Bitcoin and Ripple(XRP)

Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
0	12	-10438.114		67.6234	12.53
1	15	-10405.445	0.03106	2.2850*	3.84
2	16	-10404.303	0.00110		

Maximum rank	Parms	LL	Eigenvalue	Max statistic	5% critical value
0	12	-10438.114		65.3383	11.44
1	15	-10405.445	0.03106	2.2850*	3.84
2	16	-10404.303	0.00110		

Bitcoin and XRP Number of obs: 2071

Sample: 5-2075 Lags: 4

Trend: none

Table 7. Johansen test for cointegration between Bitcoin and EOS

Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
0	8	-5359.9046		12.3926*	12.53
1	11	-5354.3432	0.01710	1.2699	3.84
2	12	-5353.7083	0.00197		

Maximum rank	Parms	LL	Eigenvalue	Max statistic	5% critical value
0	8	-5359.9046		11.1227*	11.44
1	11	-5354.3432	0.01710	1.2699	3.84
2	12	-5353.7083	0.00197		

Bitcoin and EOS — Number of obs: 645

Sample: 4-648 — Lags: 3

Trend: none

Table 8. Johansen tests for cointegration between Bitcoin and Litecoin

Maximum rank	Parms	LL	Eigenvalue	Trace statistic	5% critical value
0	12	-20900.56		69.7937	12.53
1	15	-20867.062	0.03042	2.7967*	3.84
2	16	-20865.663	0.00129		

Maximum rank	Parms	LL	Eigenvalue	Max statistic	5% critical value
0	12	-20900.56		66.9970	11.44
1	15	-20867.062	0.03042	2.7967 *	3.84
2	16	-20865.663	0.00129		

Bitcoin and Litecoin — Number of obs: 2169

Sample: 5-2173 — Lags: 4

Trend: none

The Engle-Granger two step procedure for cointegration was also performed. The results showed that four of the five observed pairs had a cointegrating relationship, which were the pairs of Bitcoin and the altcoins Bitcoin Cash, Ethereum, Litecoin, and XRP. There was no statistical evidence that cointegration existed between Bitcoin and EOS during the tested time period. The long term relationship between Bitcoin and Ethereum was also weak compared to the other pairs, but it still showed a cointegrating relationship at a critical value of 10% in the augmented Dickey Fuller test. Normally, the ADF-test is the unit-root test that is regarded in the Engle-Granger. The ordinary Dickey Fuller test was also performed to check the residuals for stationarity. The Dickey-Fuller test yielded similar results, but it was not possible to reject the null-hypothesis of a unit-root in the DF-test for Bitcoin and Ethereum, even though it was very close. The null-hypothesis of a unit root could be rejected for all other pairs that showed a cointegrating relationship, which meant that the residuals were stationary.

In summary, this concludes that there is cointegration among Bitcoin and the alternative cryptocurrencies Bitcoin Cash, Ethereum, Litecoin and XRP. Neither the result from Johansen's test for cointegration nor the Engle-Granger test showed that Bitcoin and EOS were cointegrated. This seems reasonable, since the prices of Bitcoin and EOS did not appear to have a long-run relationship in figure 4.

In order to estimate the long-run relationship between the time series that were cointegrated, a vector error-correction model is used. The VECM included the same number of lags as the Johansen test and was modelled with no trend. The altcoins are positioned as the dependent value and Bitcoin as the independent value in the VECM. Information about the sample can be found in the header and the first estimation table provides knowledge about the short-run dynamics of the model. The second estimation table holds information about the estimated parameters of the cointegrating vector of the model. It also contains the standard errors, the z-statistic and confidence intervals for the cointegrating vector. Statistically significant results, with a p-value lower than 5%, are denoted by an asterisk. Only the result from the second table will be reported in this section in tables 9 to 12. The complete result can be found in the appendix.

Table 9. Cointegrating equations for Bitcoin Cash and Bitcoin

Equation	Parms	chi2	P>chi2

_ce1	1	178.2921	0.0000*

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_ce1						
closebitcoincash	1	.	.	.	.	
closebitcoin	-.1251687	.0093741	-13.35	0.000*	-.1435416	-.1067958

Table 10. Cointegrating equations for Ethereum and Bitcoin

Equation	Parms	chi2	P>chi2
_ce1	1	218.0626	0.0000*

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_ce1						
D_closeethereum	1	.	.	.	.	
closebitcoin	-.062723	.0042475	-14.77	0.000*	-.071048	-.054398

Table 11. Cointegrating equations for Litecoin and Bitcoin

Equation	Parms	chi2	P>chi2
_ce1	1	836.3264	0.0000*

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_ce1						
D_closelitecoin	1	.	.	.	.	
closebitcoin	-.0144997	.0005014	-28.92	0.000*	-.0154824	-.013517

Table 12. Cointegrating equations for Ripple (XRP) and Bitcoin

Equation	Parms	chi2	P>chi2
_ce1	1	265.565	0.0000*

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_ce1						
D_closexrp	1	.	.	.	.	
closebitcoin	-.0000795	4.88e-06	-16.30	0.000*	-.0000891	-.00007

The error correction term _ce1 can be found in the tables. The model estimates the long-run parameter β. From the result it is concluded that the closing price of Bitcoin has a positive effect on the closing price of Bitcoin Cash, Ethereum, Litecoin and XRP in the long-run. The long-run coefficients are statistically significant at a level of 1% for all four pairs. The result for XRP and Bitcoin in table 12 suggests that there is strong support for a cointegrating equation such that

$$D\_closexrp - .00008 closebitcoin \tag{10}$$

should be a stationary series. The coefficient on D_closexrp has been normalized to 1. According to equation (10), a one dollar increase in the price of Bitcoin results in an increase in the price of XRP by 0.00008 USD.

The coefficients on L._ce1 are the parameters in the matrix α. The adjustment terms can be found in the appendix and in table 13. All the adjustment terms are statistically significant at 1% significance level, except for (-0.738) which is not statistically significant. The adjustment term (-0.057) suggests that the previous deviations from the long-run equilibrium are corrected for at a speed of convergence of 5.7%. The larger the adjustment coefficient, the more rapid is the correction to the long-run equilibrium.

Table 13. The estimation of $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}$

	Bitcoin Cash and Bitcoin	Ethereum and Bitcoin	Litecoin and Bitcoin	XRP and Bitcoin
β	$(1, -0.125)$	$(1, -0.063)$	$(1, -0.015)$	$(1, -0.00008)$
α	(-0.057, -0.738)	(-0.026, -0.214)	(-0.4997, -1.553)	(-0.042,-145,58)

6. Conclusion

The purpose of this research was to examine if there exists a long-run relationship between the first and widely known cryptocurrency Bitcoin and five of the most common cryptocurrencies. In order to examine if there was cointegration, two different cointegration tests were conducted; the Johansen test for cointegration and the Engle-Granger approach. The result of the Johansen cointegration test indicated that there was cointegration between four out of five pairs. Bitcoin and EOS was the only pair that did not have statistically significant cointegration. The result was confirmed by the Engle-Granger test, which also showed that four out of five pairs had a long-run relationship and were cointegrated, with Bitcoin and EOS being the exception. A Vector Error Correction Model (VECM) was conducted to estimate the long-run relationship between the four pairs that had shown a cointegrating relationship in the two cointegration tests. The result from the VECM suggests that the Bitcoin price has a statistically significant impact on the prices of Bitcoin Cash, Ethereum, Litecoin and XRP in the long-run. The findings are consistent with previous studies on cointegration among cryptocurrencies by Leung and Nguyen (2018), Ciaian, Rajcaniova and Kancs (2018) and Van den Broek (2018), since cointegrated cryptocurrencies were found in the studies.

The research was limited to the cointegration between Bitcoin and five alternative cryptocurrencies. The aim of the study was to investigate if there was a long-run relationship between Bitcoin and the other cryptocurrencies, which is the reason why two different tests for cointegration were performed. It would have been possible to continue the study by analyzing the short-run dynamics of the VECM and interpreting the parameters in the first estimation table. This describes at which rate short-run deviations return to the long-run equilibrium. Further research could investigate if there is a cointegrating relationship among multiple cryptocurrencies, since it is possible that there is some other cryptocurrency than Bitcoin that have an impact on the prices of the alternative coins. The time series between the five pairs were different in this study, but future studies could analyze shorter time periods, where data is available for all cryptocurrencies. Daily closing price was the historical data that was used in this study, but further researches could for instance examine hourly prices. This would provide an interesting aspect on the relationship between the cryptocurrencies.

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Appendix

Descriptive data for Bitcoin and Ethereum from 7th of August 2015 to 9th of April 2019.

Variable	Obs	Mean	Std.Dev	Min	Max
closebitcoin	1,342	3625.744	3762.654	210.49	19497.4
closeethereum	1,342	205.0725	265.4142	.434829	1396.42

Descriptive data for Bitcoin and Ripple (XRP) in the time period August 4 2013 to April 9 2019.

Variable	Obs	Mean	Std.Dev	Min	Max
closebitcoin	2,075	2489.675	3396.248	102.8	19497.4
closexrp	2,075	.1738322	.3342916	.00281	3.38

Descriptive data for Bitcoin and Bitcoin Cash from July 23 2017 to April 9 2019.

Variable	Obs	Mean	Std.Dev	Min	Max
closebitcoin	626	6856.099	3216.195	2529.45	19497.4
closebitcoincash	626	759.2421	631.1049	77.37	3923.07

Descriptive data for Bitcoin and EOS in the time period June 1 2017 to April 9 2019.

Variable	Obs	Mean	Std.Dev	Min	Max
closebitcoin	648	6706.156	3261.069	1929.82	19497.4
closeeos	648	5.61075	4.160774	.493225	21.54

Descriptive data for Bitcoin and Litecoin with data from April 28 2013 to April 9 2019.

Variable	Obs	Mean	Std.Dev	Min	Max
closebitcoin	2,173	2382.22	3355.394	68.43	19497.4
closelitecoin	2,173	31.8678	52.7807	1.16	358.34

Stationarity test

Bitcoin

Selection-order criteria

Sample: 5 - 2075							Obs =	2071
lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-19777.2				1.2e+07	19.1002	19.1012	- 19.1029
1	-14253.3	11048	1	0.000	55755.6	13.7666	13.7686	13.7721
2	-14247.2	12.246*	1	0.000	55480.5	13.7617	13.7647*	13.7698*
3	-14246	2.3898	1	0.122	55470*	13.7615*	13.7655	13.7724
4	-14245.9	.22757	1	0.633	55517.5	13.7623	13.7673	13.7759

Endogenous: closebitcoin

Exogenous: _cons

Dickey-Fuller test for Bitcoin

Dickey-Fuller test for unit root Number of obs = 2172

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.561	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.5033

Augmented Dickey-Fuller test for Bitcoin

Augmented Dickey-Fuller test for unit root Number of obs = 2071

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.608	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.4798

Ethereum

Selection-order criteria

Sample: 5 - 1342							Obs	= 1338
lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-9366.62				70583.5	14.0024	14.0039	14.0063
1	-6002.68	6727.9*	1	0.000	462.998	8.9756	8.97851*	8.98337*
2	-6001.16	3.034	1	0.082	462.64*	8.97483*	8.97919	8.98648
3	-6001.14	.02912	1	0.865	463.322	8.9763	8.98212	8.99184
4	-6000.97	.35069	1	0.554	463.894	8.97753	8.98481	8.99696

Endogenous: closeethereum

Exogenous: _cons

Dickey-Fuller test for Ethereum

Dickey-Fuller test for unit root Number of obs = 1341

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.578	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.4945

Augmented Dickey-Fuller test for Ethereum

Augmented Dickey-Fuller test for unit root lags (2) Number of obs = 1339

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.637	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.4637

Ripple (XRP)

Selection-order criteria

Sample: 5 - 2075 Obs = 2071

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-670.33				.111966	.648315	649313	.651036
1	3617.93	8576.5	1	0.000	.001782	-3.49197	-3.48997	-3.48653
2	3624.37	12.866	1	0.000	.001773	-3.49722	-3.49422	-3.4891*
3	3627.21	5.6907	1	0.017	.00177	-3.499	-3.49501	-3.48811
4	3630.3	6.1683*	1	0.013	.001766*	-3.501*	-3.496*	-3.4874

Endogenous: closexrp

Exogenous: _cons

Dickey-Fuller test for XRP

Dickey-Fuller test for unit root Number of obs = 2074

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.879	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0478

Augmented Dickey-Fuller test for XRP with 4 lags

Augmented Dickey-Fuller test for unit root lags(4) Number of obs = 2070

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.548	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0068

Augmented Dickey-Fuller test for XRP with 2 lags

Augmented Dickey-Fuller test for unit root lags(2) Number of obs = 2072

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.267	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0163

Bitcoin Cash

Selection-order criteria

Sample: 5 - 626 Obs = 622

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-4893.8				400691	15.7388	15.7416	15.746
1	-3788.3	2211	1	0.000	11493.2	-12.1874	12.1929	12.2016*
2	-3788	.50483	1	0.477	11520.8	12.1898	12.1981	12.2112

3	-3782	12.125	1	0.000	11334.8	12.1735	12.1846	12.202
4	-3779.9	4.1156*	1	0.042	11396.3*	12.1701*	12.184*	12.2057

Endogenous: closebitcoincash

Exogenous: _cons

Dickey-Fuller test for Bitcoin Cash

Dickey-Fuller test for unit root Number of obs = 625

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.096	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.2460

Augmented Dickey-Fuller test for Bitcoin Cash

Augmented Dickey-Fuller test for unit root lags(4) Number of obs = 621

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	- 1.691	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.4357

Litecoin

Selection-order criteria

Sample: 5 - 2173 Obs = 2169

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC

0	-11681				2790.81	10.772	10.7729	10.7746
1	-6581.3	10200	1	0.000	25.3422	6.07035	6.07226	6.07423
2	-6575.9	10.634	1	0.01	25.2416	6.06637	6.06925	6.07423
3	-6572.9	6.2303	1	0.013	25.1924	6.06442	9.06825	6.0749
4	-6566.6	12.537*	1	0.000	25.0703*	6.05956*	6.06435*	9.07266*

Endogenous: closelitecoin

Exogenous: _cons

Dickey-Fuller test for Litecoin

Dickey-Fuller test for unit root Number of obs = 2172

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.132	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.2319

Augmented Dickey-Fuller test for Litecoin

Augmented Dickey-Fuller test for unit root lags(4) Number of obs = 2168

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.235	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.1937

EOS

Selection-order criteria

Sample: 5 - 648 Obs = 644

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1832.4				17.389	5.69371	5.69641	5.70065
1	625.253	2414.2*	1	0.000	.410702*	1.94799*	1.95337*	1.96187*
2	-624.92	.66595	1	0.414	.411554	1.95006	1.95814	1.97087
3	-624.66	.51305	1	0.474	.412505	1.95237	1.96314	1.98012
4	-624.57	.18602	1	0.666	.413669	1.95519	1.96865	1.98987

Endogenous: closeeos

Exogenous: _cons

Dickey-Fuller test for EOS

Dickey-Fuller test for unit root Number of obs = 647

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.133	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.2314

Augmented Dickey-Fuller test for EOS

Augmented Dickey-Fuller test for unit root lags(1) Number of obs = 646

Interpolated Dickey-Fuller --------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-1.974	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.2980

Lag-selection for Johansen's test

Bitcoin and XRP

Selection-order criteria

Sample: 5 - 2075 Number of obs = 2071

lag	LL	LR	Df	p	FPE	AIC	HQIC	SBIC
0	-19060.3				338745	18.4088	18.4108	18.4142
1	-10510.2	17100	4	0.000	88.2314	10.1557	10.1617	10.172
2	-10480	60.406	4	0.00	86.0268	10.1304	10.1404	10.1576
3	-10408.2	143.68	4	0.000	80.5715	10.0649	10.0789*	10.103*
4	-10402.4	11.553*	4	0.021	80.4334*	10.0632*	10.0811	10.1122

Endogenous: closebitcoin closexrp

Exogenous: _cons

Bitcoin and EOS

Selection-order criteria

Sample: 5 - 648 Number of obs = 644

lag	LL	LR	Df	p	FPE	AIC	HQIC	SBIC
0	-7798.02				1.1e+08	24.2237	24.2291	24.2376
1	-5351.75	4892.6	4	0.000	57711.7	16.639	16.6551*	16.6806*
2	-5348.94	5.6261	4	0.229	57924.9	16.6427	16.6696	16.712
3	-5342.16	13.544*	4	0.009	57428.5*	16.634*	16.6717	16.7312
4	-5341.88	.57407	4	0.966	58094.6	16.6456	16.694	16.7705

Endogenous: closebitcoin closeeos

Exogenous: _cons

Bitcoin and Bitcoin Cash

Selection-order criteria

Sample: 5 - 626 Number of obs = 622

lag	LL	LR	Df	p	FPE	AIC	HQIC	SBIC
0	-10263.1				7.4e+11	33.0067	33.0122	33.0209
1	-8375.53	3775.1	4	0.000	1.7e+09	26.9503	26.9669	26.993
2	-8347.67	55.729	4	0.000	1.6e+09	26.8735	26.9012	26.9448

3	-8330.52	34.286	4	0.000	1.5e+09	26.8313	26.87	26.931*
4	-8318.81	23.43*	4	0.034	1.5e+09*	26.8065*	26.8563*	26.9347

Endogenous: closebitcoin closebitcoincash

Exogenous: _cons

Bitcoin and Litecoin

Selection-order criteria

Sample: 5 - 2173 Number of obs = 2169

lag	LL	LR	Df	p	FPE	AIC	HQIC	SBIC
0	-29965.4				3.4e+09	27.6325	27.6344	27.6377
1	-21006	17919	4	0.000	890116	19.3749	19.3806	19.3906
2	-20947.4	117.27	4	0.000	846386	19.3245	19.3341	19.3507
3	-20905.2	84.388	4	0.000	817097	19.2893	19.3027	19.3259
4	-20863.7	82.998*	4	0.034	789327*	19.2547*	19.2719*	19.3018*

Endogenous: closebitcoin closelitecoin

Exogenous: _cons

Bitcoin and Ethereum

Selection-order criteria

Sample: 5 - 1342 Number of obs = 1338

lag	LL	LR	Df	p	FPE	AIC	HQIC	SBIC
0	-21172.2				1.9e+11	31.6505	31.6534	31.6582
1	-15247.8	11849	4	0.000	2.7e+07	22.8008	22.8096	22.8241
2	-15214.7	66.063	4	0.000	2.6e+07	22.7574	22.772	22.7963
3	-15191.3	46.762	4	0.000	2.5e+07	22.7285	22.7488*	22.7829*
4	-15186.1	10.387*	4	0.034	2.5e+07*	22.7267*	22.7529	22.7966

Endogenous: closebitcoin closeethereum

Exogenous: _cons

Engle-Granger test

Bitcoin and Ethereum

regression closebitcoin closeethereum

Source	SS	df	MS			
Model	1.5371e+10	1	1.5371e+10	Number of obs	=	1,342
Residual	3.6146e+09	1,340	2697434.84	F(1, 1340)	=	5698.28
Total	1.8985e+10	1,341	14157563.2	Prob > F	=	0.0000
				R-squared	=	0.8096
				Adj R-squared	=	0.8095
				Root MSE	=	1642.4

closebitcoin	Coef.	Std.Err.	t	P>|t|	[95% Conf. Interval]	
closeethereum	12.75583	.1689806	75.49	0.000	12.42433	13.08733
cons	1009.874	56.66446	17.82	0.000	898.7132	1121.035

Stationarity test for residuals

Augmented Dickey-Fuller test for unit root Number of obs = 1339

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.045	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0309

Dickey-Fuller test for unit root Number of obs = 1341

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.926	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0424

Bitcoin and Bitcoin Cash

. regress closebitcoin closebitcoincash

Source	SS	df	MS	Number of obs	=	626
Model	5.2919e+09	1	5.2919e+09	F(1, 624)	=	2814.93
Residual	1.1731e+09	624	1879931.06	Prob > F	=	0.0000
Total	6.4649e+09	625	10343910.1	R-squared	=	0.8185
				Adj R-squared	=	0.8183
				Root MSE	=	1371.1

closebitcoin	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
closebitcoincash	4.610657	.0869019	53.06	0.000	4.440002	4.781313
cons	3355.494	85.76941	39.12	0.000	3187.063	3523.926

Stationarity test for residuals

Augmented Dickey-Fuller test for unit root Number of obs = 623

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.282	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

Dickey-Fuller test for unit root Number of obs = 625

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value

Z(t)	-5.018	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

Bitcoin and EOS

. regress closebitcoin closeeos

Source	SS	df	MS	Number of obs	=	648
Model	2.6547e+09	1	2.6547e+09	F(1, 646)	=	405.83
Residual	4.2258e+09	646	6541526.96	Prob > F	=	0.0000
Total	6.8806e+09	647	10634569.7	R-squared	=	0.3858
				Adj R-squared	=	0.3849
				Root MSE	=	2557.6

closebitcoin	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
closeeos	486.8383	24.16647	20.15	0.000	439.384	534.2926
cons	3974.628	168.7606	23.55	0.000	3643.243	4306.014

Stationarity test for residuals

Augmented Dickey-Fuller test for unit root   Number of obs = 645

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.028	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.2745

Dickey-Fuller test for unit root   Number of obs = 647

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-2.026	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.2754

Bitcoin and XRP

. regress closebitcoin closexrp

Source	SS	df	MS	Number of obs	=	2,075
Model	1.7660e+10	1	1.7660e+10	F(1, 2073)	=	5845.22
Residual	6.2629e+09	2,073	3021201.03	Prob > F	=	0.0000
Total	2.3923e+10	2,074	11534498	R-squared	=	0.7382
				Adj R-squared	=	0.7381
				Root MSE	=	1738.2

closebitcoin	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
closexrp	8728.921	114.1721	76.45	0.000	8505.017	8952.825
cons	972.3075	43.01041	22.61	0.000	887.9594	1056.656

Stationarity test for residuals

Augmented Dickey-Fuller test for unit root Number of obs = 2072

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.003	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

Dickey-Fuller test for unit root Number of obs = 2074

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-4.888	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

Bitcoin and Litecoin

. regress closebitcoin closelitecoin

Source	SS	df	MS	Number of obs	=	2,173
Model	2.1787e+10	1	2.1787e+10	F(1, 2171)	=	17734.38
Residual	2.6671e+09	2,171	1228503.52	Prob > F	=	0.0000
Total	2.4454e+10	2,171	11258669.1	R-squared	=	0.8909
				Adj R-squared	=	0.8909
				Root MSE	=	1108.4

closebitcoin	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
closelitecoin	60.00552	.4505917	133.17	0.000	59.12188	60.88915
cons	469.9758	27.77662	16.92	0.000	415.5043	524.4474

Stationarity test for residuals

Augmented Dickey-Fuller test for unit root Number of obs = 2170

---------- Interpolated Dickey-Fuller ---------

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.137	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

Dickey-Fuller test for unit root Number of obs = 2172

	---------- Interpolated Dickey-Fuller ---------			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-5.429	-3.430	-2.860	-2.570

MacKinnon approximate p-value for Z(t) = 0.0000

Vector Error-Correction Models

Vector error-correction model for Bitcoin Cash and Bitcoin with four lags and no trend

Sample: 5 - 626	Number of obs = 622
	AIC = 26.83972
Log likelihood = -8332.154	HQIC = 26.88127
Det(Sigma_ml) = 1.48e+09	SBIC = 26.94663

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_closebitcoin~h	7	100.935	0.1241	87.1629	0.0000*
D_closebitcoin	7	416.428	0.0587	38.37095	0.0000*

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
D_closebitcoincash						
_ce1						
L1.	-.0568575	.0128	-4.44	0.000*	.0819451	-.03177
closebitcoincash						
LD.	.1106493	.043162	2.56	0.010*	0.260533	.1952453
L2D.	-.2441123	.0423227	-5.77	0.000*	-.3270633.- .1611613	
L3D.	.1596658	.0426478	3.74	0.000*	.0760776	.2432539

closebitcoin						
LD.	-.0525163	.0106288	-4.94	0.000*	-.0733484	-.0316841
L2D.	.0589412	.0109305	5.39	0.000*	.0375177	.0803646
L3D.	-.0322201	.0108577	-2.97	0.003*	-.0535009	-.0109393
D_closebitcoin						
_ce1						
L1.	-.0738315	.0528089	-1.40	0.162	-.177335	.029672
closebitcoincash						
LD.	-.6122673	.1780732	-3.44	0.001*	-.9612843	-.2632503
L2D.	-.3323381	.1746105	-1.90	0.057	-.6745684	.0098922
L3D.	.4931955	.1759516	2.80	0.005*	.1483367	.8380542
closebitcoin						
LD.	.1279941	.0438513	2.92	0.004*	.0420472	.2139411
L2D.	-.01523	.0450959	-0.34	0.736	-.1036164	.0731564
L3D.	-.0551604	.0447957	-1.23	0.218	-.1429584	.0326375

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	178.2921	0.0000*

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_ce1						
closebitcoincash	1	.	.	.	.	
closebitcoin	-.1251687	.0093741	-13.35	0.000*	-.1435416	-.1067958

Vector error-correction model for Ethereum and Bitcoin with four lags and no trend

Sample: 5 - 1342 Number of obs = 1,338

	AIC = 22.72729
Log likelihood = -15189.56	HQIC = 22.74912
Det(Sigma_ml) = 2.49e+07	SBIC = 22.78557

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_closelitecoin	7	21.1177	0.0408	56.61507	0.0000*
D_closebitcoin	7	288.413	0.0356	49.18054	0.0000*

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
D_closeethereum						
_ce1						
L1.	-.0260636	.0050532	-5.16	0.000*	-.0359677	-.0161595
D_closeethereum						
LD.	.1096889	.0331043	3.31	0.001*	.0448057	.1745721
L2D.	-.102372	.0333243	-3.07	0.002*	-.1676864	-.0370576
L3D.	.0672406	.0329792	2.04	0.041*	.0026025	.1318787
closebitcoin						
LD.	-.0077082	.0024581	-3.14	0.002*	-.012526	-.0028904
L2D.	.0106024	.0024835	4.27	0.000*	.0057348	.01547
L3D.	-.0058952	.0024628	-2.39	0.017*	-.0107222	-.0010681
D_closebitcoin						
_ce1						
L1.	-.2136592	.0690137	-3.10	0.002*	-.3489235	-.0783948
D_closeethereum						
LD.	-1.995454	.4521173	-4.41	0.000*	-2.881588	-1.109321
L2D.	.5124425	.4551219	1.13	0.260	-.37958	1.404465
L3D.	1.108952	.4504095	2.46	0.014*	.2261656	1.991739
closebitcoin						

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
LD.	.1501825	.0335716	4.47	0.000*	.0714303	.1631348
L2D.	-.0661908	.0339183	-1.95	0.051	-.1747929	-.0853935
L3D.	-.0490427	.033636	-1.46	0.145	-.061416	.0278527

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	218.0626	0.0000*

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_ce1						
D_closeethereum	1	.	.	.	.	
closebitcoin	-.062723	.0042475	-14.77	0.000*	-.071048	-.054398

Vector error-correction model for Litecoin and Bitcoin with four lags and no trend

Sample: 5 - 2173	Number of obs = 2,169
	AIC = 19.25501
Log likelihood = -20867.06	HQIC =19.26938
Det(Sigma_ml) = 778736.3	SBIC = 19.29431

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_closelitecoin	7	4.82208	0.0857	202.6579	0.0000*
D_closebitcoin	7	223.741	0.0621	143.1764	0.0000*

	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
D_closelitecoin						
_ce1						
L1.	-.0499675	.0061107	-8.18	0.000*	-.0619444	-.0379907
D_closelitecoin						
LD.	.0788968	.0259534	3.04	0.002*	.0280292	.1297645

L2D.	-.1361871	.0259926	-5.24	0.000*	-.1871317	-.0852424
L3D.	.2124532	.0260143	8.17	0.000*	.161466	.2634404
closebitcoin						
LD.	.0002623	.0005733	0.46	0.0647	-.0008614	.0013861
L2D.	.0037061	.0005714	6.49	0.000*	.0025861	.004826
L3D.	-.0043442	.0005686	-7.64	0.000*	-.0054585	-.0032298
D_closebitcoin						
_ce1						
L1.	-1.552979	.2835333	-5.48	0.000*	-2.108694	-.9972637
D_closelitecoin						
LD.	-8.165394	1.204215	-6.78	0.000*	-10.52561	-5.805177
L2D.	2.565506	1.206036	2.13	0.033*	.2017192	4.929293
L3D.	6.37004	1.207044	5.28	0.000*	4.004277	8.735802
closebitcoin						
LD.	.1656332	.026603	6.23	0.000*	.1134924	.217774
L2D.	-.0480328	.0265135	-1.81	0.070	-.0999984	.0039327
L3D.	-.0892166	.0263812	-3.38	0.001*	-.1409228	-.0375104

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	836.3264	0.0000*

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_ce1						
D_closelitecoin	1	.	.	.	.	
closebitcoin	-.0144997	.0005014	-28.92	0.000*	-.0154824	-.013517

Vector error-correction model for Ripple and Bitcoin with four lags and no trend

Sample: 5 - 2075	Number of obs = 2,071
	AIC = 10.0632
Log likelihood = -10405.45	HQIC = 10.07816
Det(Sigma_ml) = 79.27807	SBIC = 10.10402

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_closelitecoin	7	.041465	0.0406	87.28394	0.0000*
D_closebitcoin	7	226.537	0.0821	184.5762	0.0000*

	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
D_closexrp						
_ce1						
L1.	-.0420504	.0054631	-7.70	0.000*	-.0527579	-.031343
D_closexrp						
LD.	.0984322	.0229814	4.28	0.000*	.0533895	.143475
L2D.	.0460048	.0232241	1.98	0.048*	.0004863	.0915232
L3D.	.0765866	.0237967	3.22	0.001*	.0299459	.1232273
closebitcoin						
LD.	-.0000122	4.28e-06	-2.85	0.004*	-.0000206	-3.81e-06
L2D.	2.47e-06	4.17e-06	0.59	0.554	-5.71e-06	.0000107
L3D.	-9.82e-07	4.17e-06	-0.24	0.814	-9.15e-06	7.19e-06
D_closebitcoin						
_ce1						
L1.	-145.5808	29.84659	-4.88	0.000*	-204.0791	-87.08261
D_closexrp						
LD.	-612.886	125.5546	-4.88	0.000*	-858.9684	-366.8036
L2D.	1463.856	126.8806	11.54	0.000*	1215.175	1712.537

L3D.	117.6981	130.0087	0.91	0.365	-137.1142	372.5104
closebitcoin						
LD.	.1172825	.0233944	5.01	0.000*	.0714303	.1631348
L2D.	-.1300932	.0228064	-5.70	0.000*	-.1747929	-.0853935
L3D.	-.0167816	.0227731	-0.74	0.461	-.061416	.0278527

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	265.565	0.0000*

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
_ce1						
D_closexrp	1	.	.	.	.	
closebitcoin	-.0000795	4.88e-06	-16.30	0.000*	-.0000891	-.00007