Erasmus University Rotterdam

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Bachelor Thesis General Economics

Cointegration-based pairs trading framework with application to the Cryptocurrency market

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Abstract

This research examines the possibilities of pairs trading in the newest, unexplored financial market: the cryptocurrency market. By applying the Engle-Granger 2-Step Method, cointegrated cryptocurrency pairs are identified. Next, profitability of four arbitrarily selected pairs is tested by using pairs trading with a set of trading criteria. In a 60-day trading period all four pairs show profitability, arising from arbitrage opportunities in the cryptocurrency market. Therefore, this research concludes that the Efficient Market Hypothesis does not hold for the cryptocurrency market.

Keywords: Pairs Trading, Cointegration Method, Cryptocurrency, Spread, Distance Method, Time Series

About cointegration.

A drunk and his dog leave the bar after a night of drinking. The path of the drunk looks much like a random walk. The dog follows, but is slow and falls behind of its owner. The dog will go this way and that, wherever it's nose leads it. However, whenever she falls behind too much the drunk calls for the dog. The dog is loyal and catches up with the owner. So the drunk and his dog go forth wandering aimlessly at night, together.

by Michael P. Murry

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1 Introduction

According to the Efficient Market Hypothesis (EMH) asset prices fully reflect all past and current publicly available information (Fama, 1970). However, in practice, markets have shown to not be perfectly efficient, and even the weakest form[1] of the EMH does not seem to hold (Nicholson, 1968), (Basu, 1977), (Rosenberg et al., 1985). All sort of events, such as changes in demand and supply or unexpected news, are not efficiently incorporated in an assets price, making an assets price temporarily diverge from its equilibrium price. During this period of misalignment short term arbitrage opportunities exist for market participants (arbitrageurs). Different strategists apply different tactics in order to detect and exploit these market anomalies. One of the strategies known as pairs trading is presented and discussed in this research.

It was in the early to mid-1980s when Nunzio Tartaglia's trading group at Wall Street's Morgan Stanley & Co brought together a group of mathematicians, physicists and computer scientists, with the goal of exploiting financial market imbalances. The trading strategy they presented is known as pairs trading. Even though pairs trading appears to be simplistic at first sight, complex econometric techniques can be applied to execute pairs trading. This explains, why since its birth this strategy has been widely adopted by hedge funds, investment banks and traders (Bookstaber, 2006). The essence behind pairs trading is characterized by selecting a pair of assets of which the spread, defined as the difference in prices between the paired assets, has the property of mean-reversion. In practice the trading rule that forms the backbone of pairs trading is as follows. When the spread diverges from its mean the investors sets a position by shorting the overvalued asset and going long on the undervalued asset. Once the spread converges back to its mean the investor should liquidate the position, resulting in a profit. Also, a position can be taken when the spread reaches the mean, followed by rewinding the position when the spread diverges adequately (Skiena, 2008).

Pairs trading is a strategy that is applicable in a wide array of financial markets. At first mostly exercised in the US equity market, empirical research discovered its usability in various financial markets such as the foreign exchange market and option market (Caporale et al., 2017), (Yang et al., 2017). This research applies the pairs trading strategy to one of the newest, unexplored, financial markets known as the cryptocurrency market. Given that EMH does not hold in conventional markets, the purpose of this paper is to determine whether EMH holds in the cryptocurrency market. If the EMH does not hold, then pairs trading could be a way to profit from arbitrage opportunities arising from market inefficiencies.

[1]The EMH consist of three levels of efficiency; Strong, Semi-strong and Weak. The Strong form assumes private information is fully reflected in the market. The Semi-strong form assumes any released public information gets directly incorporated in market prices. The Weak form assumes all past information is reflected in market prices and future prices follow a random walk (Fama, 1970).

The Cryptocurrency market

A cryptocurrency is a digital asset with the purpose to serve as a medium of exchange, functioning in a similar manner as fiat currencies (currencies declared to be legal tender, i.e. EURO or USD). The source of every cryptocurrency is a so-called blockchain, which is defined as; *"an open distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way"* (Iansiti and Lakhani, 2017). The idea of a blockchain was first described by Nakamoto (2008), who introduced Bitcoin, a peer-to-peer digital electronic cash system.

Bitcoin is the most prominent cryptocurrency and peaked at dominating the cryptocurrency market at a staggering 95% of the complete market capitalization in the last quarter of 2016. As Bitcoin became more popular, it caught the attention of developers and companies, who altered and refined the underlying technology to create new, different and advanced cryptocurrencies, known as alternative cryptocurrencies. This advancement accelerated at the beginning of 2017. The cryptocurrency market as a whole started to grow exponentially as more and more fiat money started to pour in. With the boom of alternative cryptocurrencies, the cryptocurrency market became more diversified. Bitcoin stayed the prominent cryptocurrency, due to its first-mover advantage, but lost a large amount of its dominance, with the lowest dominance point being around 30-40% (Coinlib).

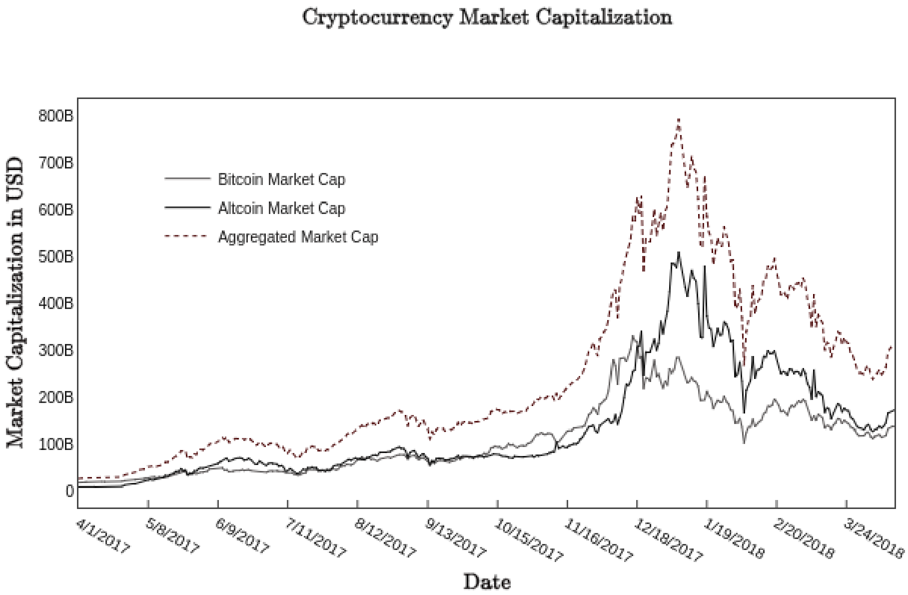


Figure 1: Illustration of the Cryptocurrency Market Capitalization. In early 2017 the market held a total capitalization of $18 billion and peaked at the first quarter of 2018 with a market capitalization of $800 billion.

The cryptocurrency market characterizes itself as a volatile space, especially when compared to conventional markets. While stocks or bond markets deal on average with no more than single percent digit price movements per day, cryptocurrencies can experience double or triple digit price movements, upwards and downwards. The volatile and, current, non-regulatory , nature calls into question whether cryptocurrencies are a viable addition to one's asset portfolio. The advantage of this new developing asset class brings is potential portfolio diversification. Cryptocurrencies distance themselves from fiat, after all, they profile themselves as an alternative to fiat (McDonnell, 2015). This characteristic makes cryptocurrencies potentially less susceptible for shocks in the traditional market, making them a hedge option. Furthermore, cryptocurrencies are traded on digital exchanges that do not operate with a closing or opening time. Cryptocurrency-exchanges are open 7 days a week, 365 days a year. Being able to trade at any time of the day or night brings a bigger window of opportunity to make trades.

The remainder of the research is organized as follows. In section 2 existing literature on pairs trading is reviewed. Section 3 explains the methodology used in this research. Section 4 gives a description of the data used and is followed by a discussion of the results in section 5. Finally, section 6 concludes the research and expands on shortcomings and possible future research.

2 Literature

Mainly due to the proprietary nature of the area, published research on pairs trading has been largely limited. Three of the most cited papers in the context include Gatev et al. (1999), Vidyamurthy (2004) and Elliott et al. (2005) that propose methods applicable for pairs trading. An overview of these three meaningful papers is presented below.

The first, most renowned, paper on this subject is an empirical piece of research by Gatev et al. (1999). They introduce the distance method, a non-parametric framework in which pairs are formed by measuring the co-movement of two assets by a so-called distance, which is measured as the sum of squared differences between the two normalized historical prices over a predetermined time frame. An asset is paired with a matching partner when their distance is relatively small. A trade is executed when the spread diverges at least two standard deviations from its mean. By using this simple standard deviation strategy, Gatev et al. (1999) achieve profits net exceed transaction costs thus creating a net profitable strategy. Seven years later they followed up on their earlier piece using a more recent dataset and confirmed once again net profitability of this method (Gatev et al., 2006).

The profitability in the latter paper of Gatev et al. (2006) decreased compared to the findings from 1999. The underlying reason suggested by Gatev et al. (2006) was an increase in hedge fund activity, which exploit and exhaust these arbitrage opportunities. Do and Faff (2010) performed a related study using the same methodology on an extended trading period and found likewise smaller returns. However, they argued these smaller returns were due to an increased fundamental risk of the pairs trading strategy referred to by them as *"the possibility of an unexpected disruption in the relative relationship between paired assets"*. When there is a lack of equilibrium relationships among the pairs a larger number of pairs do not converge back. As a result, opened pair trades have to be closed at a loss. In the case of Do and Faff (2010), they find that 32% of the pairs do not converge back, which reveals a flaw in identifying pairs based on the distance metric since pairs that not converge back are a huge drawback.

Vidyamurthy (2004) proposes the implementation of a cointegration-based framework for pairs trading. The cointegration method is characterized by two main advantages: it confirms the property of mean-reversion of the pair and uses statistics to reason the choice of a pair (Engle and Granger, 1987). As his method uses a cointegration approach it is one of the first parameterized methods. The cointegration method has shown to give more consistent and robust pairs. Caldeira and Moura (2013) document excess returns of 16% per year on a Brazilian stock index, using the cointegration method. Moreover, Huck and Afawubo (2015) find excess returns of 5%, on a monthly basis on an S&P 500 index.

Elliott et al. (2005) expand the pairs trading literature by introducing a parameterized method known as the stochastic spread method, which makes use of the Kalman filter. The Kalman filter, introduced in 1960 by Rudolph E. Kalman, is one of the most well-known and commonly used tool for stochastic estimation from noisy sensor measurements (Welch and Bishop, 2001), (Kalman, 1960). Widely used in aero-space related fields the Kalman filter made its way into quantitative finance. The Kalman filter is adopted in pairs trading to obtain the true state of the spread of a pair. Once the true state of the spread is estimated, a trading action can be executed when the observed state differs from the true state. By using the Kalman Filter for pairs trading, the true state resembles an estimation of what the value of the spread is expected to be. The observed state relates to the observed value of the spread. The difference between the true and observed state can be explained by i.e. random white noise in a financial market. Elliott et al. (2005) apply the Kalman filter to capture the properties of the spread related to its mean-reversion tendency and to, consequently, make the appropriate investment decisions.

The distance method and cointegration methods focus solely on the pair formation process. For the trading part of pairs trading, Gatev et al. (2006) propose a simple, ad-hoc trading strategy by executing a trade whenever the spread deviates two or more historical standard deviations from its historical mean. However, the optimal point in time to execute a trade might be earlier or later. A solution is the stochastic spread method, which can be used to predict when the spread is about to mean revert, in order to optimize the execution of trades thus resulting in increased profitability. The stochastic spread method is beyond the scope of this thesis and is left for future research. The pair formation method and trading strategy used in this research is discussed in the methodology section.

Pairs trading is mostly exercised on the asset class stocks. However, the strategy can also be applied on other securities. Caporale et al. (2017) apply pairs trading to the foreign exchange market, and find evidence supporting profitability of pairs trading. Beside the findings of Caporale et al. (2017) there is plenty of evidence that pairs trading allows to make abnormal returns in various financial markets (Papadakis and Wysocky, 2007), (Engelberg et al., 2009), (Jacobs and Weber, 2013), (Jacobs and Weber, 2015), (Huck, 2013), (Chen et al., 2012), (Yang et al., 2017). With results confirming the adaptability of pairs trading, this research attempts to assess whether this strategy can be applied in one of the newest, unexplored, financial markets; the cryptocurrency market. Additionally, in the case EMH does not hold for the cryptocurrency market, arbitrage opportunities exist to profit from. This should be reflected in the results of the profitability of pairs trading in the cryptocurrency market.

Along with the development of the cryptocurrency market, naturally, the academic research around cryptocurrencies also increased. However, the academic literature on cryptocurrencies is primarily focused on the ethical (Angel and McCabe, 2015) or legal (Plassaras, 2013) aspects of this new digital asset. Research on the financial or economic aspect of cryptocurrencies is highly limited and mostly covers only the economics behind Bitcoin. Polasik et al. (2015) look at the relation between Bitcoin's price and media attention. Brière et al. (2015) find evidence that the risk-return trade-off of diversified portfolios can be improved greatly by investing in Bitcoin. The discussed pairs trading strategy has shown to be effective in multiple international markets as well as different asset markets. Seeing financial research on the cryptocurrency market, in specific alternative coins, is scarce, a study that applies pairs trading strategies to the emerging cryptocurrency field is needed. This research attempts to fill this gap in the literature.

Research Questions

The purpose of this research is to examine the possibilities of pairs trading in the cryptocurrency market. It will primarily focus on the following two sub-questions:

1. *Are there any cointegrated pairs in the cryptocurrency market?*
2. *Does the EMH hold for the cryptocurrency market?*

By identifying cointegrated pairs the pairs trading strategy can be applied. Next, a set of trading rules is applied to pave a way to determine whether pairs trading in the cryptocurrency market is profitable. If profitability is found, it means market inefficiencies, or market anomalies, exist, making the EMH not hold for the cryptocurrency market. Indeed, this research shows that EMH does not hold for the cryptocurrency market and that there is room for arbitrage. The results of this research can be of interest to anyone that wants to research the applicability of pairs trading in the cryptocurrency market.

3 Methodology

In this section the methodology used in this research is discussed. As mentioned in the introduction there are multiple approaches to the formation of pairs. Section 3.1 outlines the distance method introduced by Gatev et al. (1999). In Section 3.2 the more sophisticated approach known as the cointegration method is discussed. Section 3.3 concludes on both methods and elaborates which method is used in this research. Furthermore, section 3.4 gives the trading rules for opening and closing a potion and discusses how returns are calculated.

3.1 Distance Method

Since its introduction by Gatev et al. (1999) the distance method has been the most intensively researched method for pairs trading and is characterized by its simplicity and transparency. The method can be divided into two steps. The first step is the formation period, in which pairs are formed. The second step is the trading period, in which positions are taken and unwound.

Formation period: Over a 12-month period pairs are formed in a way a rational pairs trader, with the objective of maximizing excess returns per pair, would try to identify pairs (Gatev et al., 1999). In each formation period all illiquid stocks, which are stocks that have one or more days with no trade, are filtered out. Next, a cumulative total returns index P_t for each stock i is constructed over the formation period. After, a matching partner for each stock is chosen by finding a stock that minimizes the sum of squared deviations between the normalized price series (Gatev et al., 1999). Gatev et al. (1999) use the Euclidean squared distance to minimize the sum of (i) spread variance and (ii) squared spread mean. Mathematically illustrated, the spread variance for two stocks, with P_{it} and P_{jt} as the normalized prices for the stocks i and j at time period t , is as follows:

$$V\left(P_{it} - P_{jt}\right) = \frac{1}{T}\sum_{t=1}^{T}\left(P_{it} - P_{jt}\right)^2 - \left(\frac{1}{T}\sum_{t=1}^{T}\left(P_{it} - P_{jt}\right)\right)^2 \tag{1}$$

The average sum of squared distances for the formation period can now be solved by adding the squared spread mean:

$$\overline{SSD_{ijt}} = V\left(P_{it} - P_{jt}\right) + \left(\frac{1}{T}\sum_{t=1}^{T}\left(P_{it} - P_{jt}\right)\right)^2 = \frac{1}{T}\sum_{t=1}^{T}\left(P_{it} - P_{jt}\right)^2 \tag{2}$$

The distance, or the (absolute) spread, equals the price difference between the two stocks defined as

$$S_{ijt} = \left(P_{it} - P_{jt}\right) \tag{3}$$

In addition to using this method to identify pairs, Gatev et al. (1999) apply sector restrictions to their results to filter pairs of stocks that belong to the same broad industry category.

Trading period: After pairs are formed they are traded in the next 6-month period. The prices of each stock are normalized to the first day of the trading period. A basic trading rule is then applied; if the spread diverges more than two historical standard deviations from the historical mean, a position is opened. At the next crossing of the prices the position unwinds.

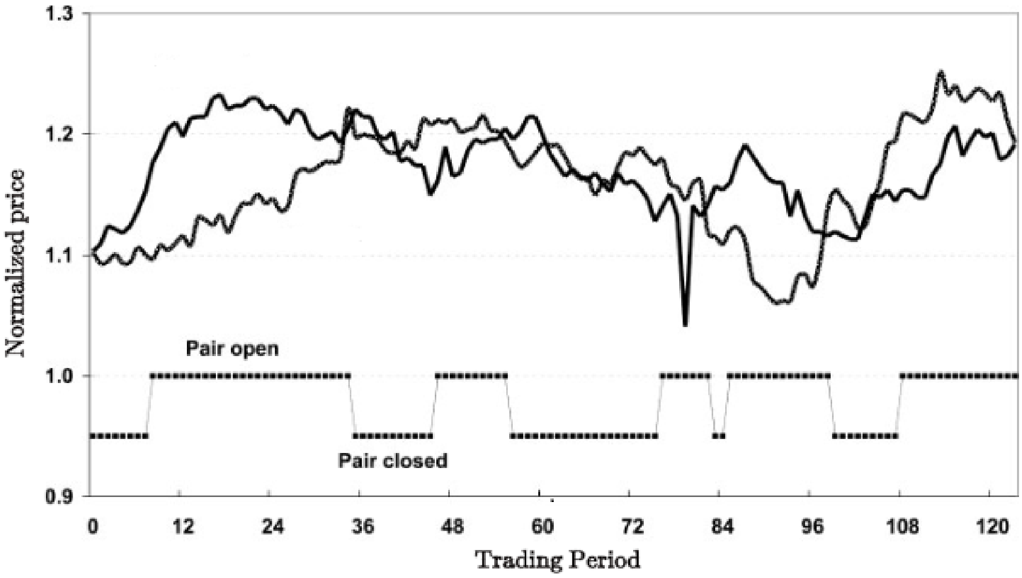


Figure 2: Example taken from Gatev et al. (1999). Daily Normalized prices of the stocks Kennecott and Uniroyal during the trading period of August 1963-January 1964. Pairs are opened when the spread diverges and are closed on convergence.

Drawbacks

The distance method has been a base for pairs trading, but as stated by Krauss (2015) is characterized by three drawbacks. First, the metric, Euclidean squared distance, used by Gatev et al. (1999) gets more optimal the lower the spreads mean variance. A lower mean variance leads to less deviations from the mean, resulting in smaller potential profits. Second, a partner is formed for every stock. This could lead to stocks being partnered just for the sake of having a partner, even though a certain stock possibly doesn't qualify to pair with any stock at all. These 'forced' pairs might be suboptimal, ending up in a loss during the trading period. Third, the pairing of stocks can not be reasoned statistically. Gatev et al. (1999) do not look at a long-run equilibrium relationship or at mean-reversion properties of the pairs. This could overall lead to a higher number of pairs that do not converge back to their mean.

3.2 Cointegration Method

Vidyamurthy (2004) explored a cointegration approach to form pairs in a statistical way. Introduced by Engle and Granger (1987), cointegration describes a relationship between two time series, or in this case two stocks, with the properties of mean-reversion and a similar long-run trend. In order for two time series to be cointegrated certain conditions need to be met. For example, the log prices of two stochastic price series P_{it} and P_{jt} are both integrated of order 1, $I(1)$. This means both series contain a unit root, i.e. both series are non-stationary. When the price series are cointegrated, there exists a linear relationship that would define an equilibrium. This linear relationship is defined, with coefficient β and intercept a, as follows:

$$P_{it} = a + \beta P_{jt} + u_t \tag{4}$$

Where a and β_j are estimated parameters. The residuals, u_t, in (4), are the same as the spread between two assets in pairs trading. In order to test for cointegration the Engle-Granger 2-step procedure is used. To start, both price series are tested for order 1 integration by testing for unit roots. Given both price series pass the test and are non-stationary, the parameters in the defined regression equation (4) are estimated using an *Ordinary Least Squares* regression (OLS). Next, the residuals (or spread), $\hat{u}_t$, are tested for stationarity by using the *Augmented-Dickey-Fuller* test (ADF-test) (Dickey and Fuller, 1979). The ADF-test can be used to test for a unit root in a univariate process in the presence of serial correlation. The null hypothesis of the ADF is that there is a unit root, with the alternative that there is no unit root[2]. If the null hypothesis of a unit root in the residuals is rejected the two variables are cointegrated.

Furthermore, when testing for cointegration via the Engle-Granger 2-step procedure, the order of the variables matters. Testing for cointegration for (A, B) can give different results compared to testing for (B, A), therefore Coint$(A, B) \neq$ Coint(B,A). For this reason the total amount of pairs are the total amount of permutations (See Appendix A; Supplementary Equations for the underlying math)[3].

3.3 Choice of method

Even though Vidyamurthy (2004) does not provide any empirical results, numerous other papers provide compelling numbers finding evidence that the cointegration method works in a superior (profitwise) way compared to the distance method (see *Literature* section).

Since the cointegration method is statistical and found to be a more robust and mathematically advanced method, it is be the primary method for identifying pairs in this research. Additionally,

[2]Definition by Statsmodels, a statistical module for Python used in this research.

[3]The function statsmodels.tsa.stattools.coint is used for iterating over all permutation to find cointegrated pairs. The function comes in the form of Coint(A, B) with A being the first element of the cointegrating vector, and B being the remaining element of the cointegrating vector.

the Engle-Granger Two step method is also widely available for use in electronic packages, such as the statistics module *Statsmodels* for Python. Python is a programming language suitable for a wide range of applications such as data analytics and is used in this research. This greatly enhances the ease-of-use for the pairs selection process, especially when re-applying this method in future research.

3.4 Trading Rules

After pairs are found via the cointegration method over the formation period, an arbitrary amount is hand-selected and traded over a period of 60 days, starting right after the formation period. By doing so, the fitted model from the formation period is checked by a cross-validation out of sample. Based on the framework by Gatev et al. (1999) a set of trading rules are formed. Instead of taking the absolute spread between two cryptocurrencies, the Z-score is calculated over the spread to normalize the trading signals. Additionally, the Engle-Granger method is applied (Engle and Granger, 1987). A linear regression (via OLS) is used to get the hedge ratio, or β coefficient, between the two cryptocurrencies. Accordingly, computing the spread, S_{ijt}, is as follows:

$$S_{ijt} = P_{jt} - \beta P_{it} \tag{5}$$

Afterwards, the Z-score is computed, with spread S_{ijt}, for assets i and j with time t, as follows (Pelletier, 2007):

$$Z_t(S_{ijt}) = \frac{S_{ijt} - \left(\frac{1}{T}\sum_{t=1}^{T}(S_{ijt})\right)}{\sqrt{\frac{1}{N}\sum_{t=1}^{T}(S_{ijt} - \left(\frac{1}{T}\sum_{t=1}^{T}(S_{ijt})\right))}} \tag{6}$$

or denoted with the mean and standard deviation (σ) notation:

$$Z_t(S_{ijt}) = \frac{S_{ijt} - \overline{S_{ijt}}}{\sigma_{S_{ijt}}} \tag{7}$$

Consequently, the threshold for opening a position and unwinding a position is set as follows. If the Z-score diverges 2 historical standard deviations then a position is opened. Next, if the Z-score converges back and falls below 1 historical standard deviation then the position is unwound.

Calculating the return

The value created by applying pairs trading is calculated by a using Marked-to-Market (MTM) pnl (profit and losses). As an example; consider the pair (i_t,j_t) with the following numbers at moment t_1 when the Z-score diverges and breaks the two historical standard deviations;

$$P_{it_1} = \$272,73 \; P_{jt_1} = \$462,76 \; \beta = 1.93$$
$$\text{which gives } S_{ijt_1} = -63,61$$

A position is opened; coin i is shorted for \$272,23 x 1.93 = \$526,37 (+) and a long in coin j for \$462,76 (-), which results in a MTM pnl at the end of the day of \$63,61 At moment t_2 the spread converges again and falls below the 1 historical standard deviations, consider the following numbers:

$$P_{it_2} = \$267.93 \; P_{it_2} = \$504.34 \; \beta = 1.93$$
$$\text{which gives } S_{ijt_2} = -12,76$$

The positions are closed, giving a cash inflow by selling the long position with coin j of \$504,34 (+) and a cash outflow for settling the short of coin i for \$267,93 x 1.93 = \$517,10 (-). The MTM pnl at the end of the day at moment t_2 is \$63,61 - \$12,76 = \$50.85. The profit made is the balance of the MTM pnl when the positions are unwound, in this example t_2.
In this research transactions costs and short-selling costs are not taken into account. These costs can highly differ per exchange, therefore a general estimation would be inaccurate.

4 Data

4.1 Data Source

In order to perform a pairs trading strategy, historical price data is required. However, the cryptocurrency market has been fairly recently established and as a result, conventional databases such as DataStream, Bloomberg or Yahoo Finance provide limited data with regards to historical cryptocurrency prices. Nonetheless there are databases that are less popular, but purely focused on cryptocurrency pricing data. CryptoCompare, one of the biggest data providers in the cryptocurrency space, provide a wide range of cryptocurrency pricing data. From the CryptoCompare database, live pricing data, historical OHLC (Open, High, Low, Close) data, volume data and tick data can be obtained via the use of an applicable programmable interface (API). An API allows software applications to communicate with one another. By using Python, cryptocurrency data is fetched from the CryptoCompare database through their API.

4.2 Formation Period

Estimating the optimal look-back period or formation period is not quantitatively resolvable, for example, GGR arbitrarily choose a formation period of 12 months. Caldeira and Moura (2013) apply, similarly to this research, cointegration to estimate pairs and also arbitrarily pick a 12 month formation period. However, the cryptocurrency market developed mainly throughout Q2 2017. Applying a 12 months look-back period would result in numerous alternative coins either not existing yet or not showing much to any price movement. Therefore, one period is tested to find cointegrated relationships, which is a look-back period of 210 days, starting 15 April 2018 and ending 15 September 2017.

4.3 Data filtering

To compile a robust list of cryptocurrencies for the formation period, two factors are taken into consideration: market representativity and liquidity.

Market representativity stands for the relative market capitalization the coin holds compared to the whole market. On 15 April 2018 there were a total of 1538 cryptocurrencies (coins) listed. However the majority of the total cryptocurrency market capitalization is covered by a small percentage of the total existing coins. To draw a line and avoid data snooping, this research chooses to take coins only with a minimum market capitalization of $400 million. Applying this filter gives 45 coins. On the snapshot taken on 15 April, these 45 coins represent 92% of the total cryptocurrency market capitalization (323 billion).

Further, illiquidity, a key characteristic for any trading strategy, is controlled for. Although the cryptocurrency market seems to offer a big variety of coins, most of them lack liquidity. To avoid slippage a minimum volume of \$10 million for the last 24hr on 15 April 2018 is set to minimize potential illiquidity issues when executing a trade. After filtering, the dataset consists of a total of 34 cryptocurrencies.

Additionally, the cryptocurrency Gas is added to the dataset. Regardless of this coin not meeting the two requirements of market capitalization and liquidity, Gas is expected to show cointegrated behavior with the coin NEO. Holding NEO pays out a virtual dividend in the form of Gas. Both cryptocurrencies' intrinsic value comes from the same underlying source, thus on paper it makes for an exceptional candidate for pairs trading. Including Gas, the dataset consists of 35 coins.

As last, the cryptocurrency Tether is removed from the dataset. Tether is a cryptocurrency that is pegged to the USD; every single Tether in circulation is backed by one USD (Tether). The purpose of Tether is to provide a hedge option within the cryptocurrency market and it can be used to short the cryptocurrency market. As the value of Tether fluctuates around 1 USD it means Tether is stationary, which violates the requirement of a times series to be integrated of order 1 (non-stationary) for the Engle-Granger 2-step method. Therefore Tether is filtered out, resulting in a data set of 34 coins. Table C.1 in the appendix presents an overview of the dataset. Further the pricing data used is daily historical pricing data. From the OHLC the closing prices are taken[4].

4.4 Sector Grouping

In the pair formation period GGR presents "restricted" pairs in addition to "unrestricted" pairs. Both stocks are restricted in the sense that they both belong to the same broad industry categories. Respectively, for unrestricted pairs both stocks do not necessarily belong to the same broad industry category. The underlying idea is that stocks in the same industry are more related to each other, and expect to relatively have more cointegrated pairs. Cryptocurrencies can also be placed into industry categories. In this research a distinction is made of four sectors: Application platforms, Financial Transactions, Private Digital Currency and Others. Pairs are identified in each independent sector and, additionally, pairs are also searched for cross-sector. Table 1 below gives a short description of each sector. Table C.2 in the appendix gives an overview of the size (in market capitalization) per sector. Table C.3 in the appendix lists cryptocurrencies for each sector.

[4] Cryptocurrency exchanges are open 24/7, hence a closing price is based on the value on 00:00 GMT. BTC (Bitcoin) conversion is used if data is not available, because the coin is not trading in dollars.

Table 1: Sector Description for all four sectors

Application Platform	Financial Transactions
The particular cryptocurrency is used to pay the fees for making use of the platform. Platforms allow developers to create distributed, or decentralized applications (dApps).	Cryptocurrencies that were created with the main purpose of serving for financial transactions.

Private Digital Currency	Other
Similar to Financial Transactions cryptocurrencies, they serve as a mediator for financial transactions. However, the aim is to make financial transaction 100% private.	Other stands for a basket of numerous cryptocurrencies: from Supply Chain management utility tokens to coins that give a discount when making use of a particular exchange.

5 Results

The results chapter is divided into two sections in a manner that corresponds to the research questions. Section 5.1 presents the results of an attempt to identify cointegrated pairs in the cryptocurrency market. Section 5.2 reviews the application of the trading rules on a select number of pairs and subsequently analyses the realized profit.

5.1 Cointegrated pairs

As discussed in section 4.4 all cryptocurrencies are placed into a sector. The number of pairs per sector and cross-sector is summarized in Table 2, whereas a detailed list of pairs per sector can be found in the Tables C.4, C.5, C.6, C.7 and C.8 in the appendix.

Table 2: Overview of number of cointegrated pairs and possible pairs, per sector and cross-sector

Sector	Number of pairs	Number of possible pairs	% of possible pairs
Application	7	110	0.064%
Financial	2	72	0.028%
Private	0	12	0.000%
Other	0	90	0.000%
Application & Financial	9	198	0.045%
Financial & Private	3	72	0.042%
Application & Private & Other	10	398	0.025%
Total	31	952	0.033%

As presented in Table 2, the application sector has the highest percentage of the number of possible pairs, followed by the sector financial. Noticeably, the sectors Private and Other have zero number of pairs within the sector. Furthermore, the majority of pairs are cross-sectional (see Table C.8). The percentage of the number of possible cointegrated pairs in the dataset is fairly low compared to empirical studies discussed in the literature section. However, the dataset used in the research is a lot smaller due to the cryptocurrency market being new and the limited number of established cryptocurrencies (i.e cryptocurrencies that are substantial; pass the filter criteria used in this research). Therefore, cointegrated pairs are likewise limited.

In the data section the cryptocurrency Gas was added to the data set due to the expectation that it would show cointegrated behavior with the cryptocurrency NEO. However, after testing, this assumption can be rejected: no significant p-value is found for the pair NEO & Gas.

5.2 Trading Period

When investigating the trading period the aim of this research is not to find the most profitable pairs, or the most optimal trading rules. Instead, the primary focus of this research is find evidence whether the EMH holds for the cryptocurrency market. In order to do so, the profitability of all pairs does not need to be aggregately investigated. Even one pair showing profitability gives sufficient evidence reject the EMH hypothesis. Therefore, four pairs are arbitrarily selected. Table 3 below presents an overview of the pairs.

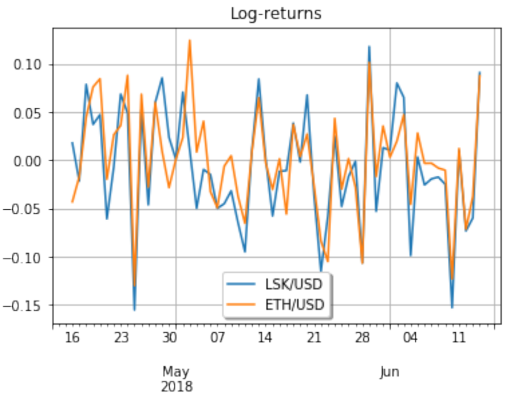
Table 3: Arbitrarily Selected Pairs

Pairs	β Coefficient*	T-Statistic	P-Statistic
LSK & ETH	0.01680	-3.4063	0.0417
ICON & LSK	0.0052	-4.4663	0.0014
LTC & XMR	0.6606	-4.0248	0.0066
XRP & XLM	2.1448	-3.7372	0.0164

*The β Coefficient is equal to the hedge ratio

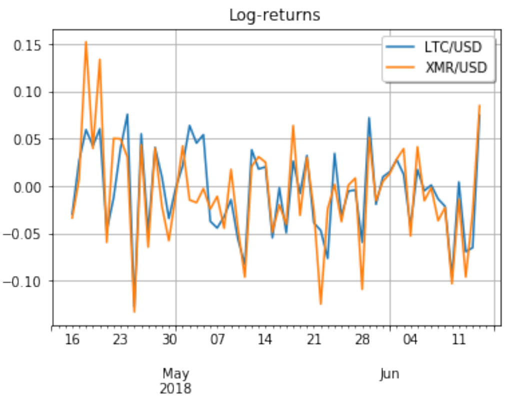
The pairs are back tested in the trading period (the 60 consecutive days after the formation period). As can be observed in Figure 3, the pairs follow fairly similar log-returns, except for the ICON & LSK pair. Out of all the coins (taken for the trading period), ICON shows volatile behavior, which is reflected in the big spikes in it's log returns. Unfortunately, no direct underlying reason can be found for these big spikes. The cumulative log-returns give an indication how the cryptocurrency market was performing during the trading period (15 April 2018 - 15 June 2018) and show a down-trend (see Figure B.1 in the appendix).

Figure 3: Pairs Log-Returns



(a) Pair: LSK & ETH

(b) Pair: ICON & LSK



(c) Pair: LTC & XMR

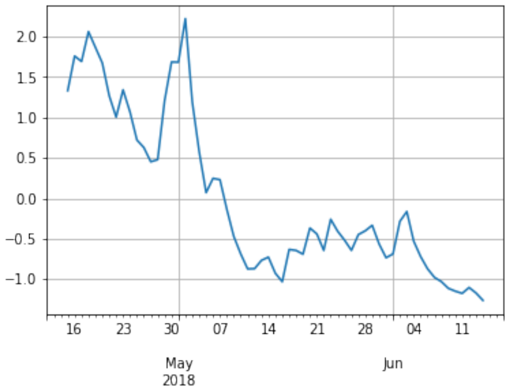
(d) Pair: XRP & XLM

Rather than plotting absolute values, log returns are plotted for clarity reasons (Log returns scale better).

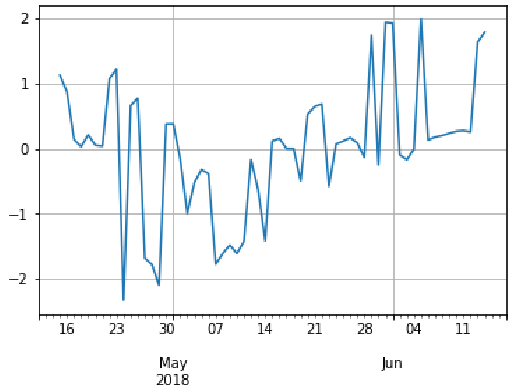
The following figures show the progress, step by step, of implementing the trading strategy.

To start, the spread is taken over the pairs to consequently calculate the Z-score over the spread for finding trading signals. In Figure 4 the Z-score over the spread is displayed (see Figure B.2 for an overview of the spread per pair).

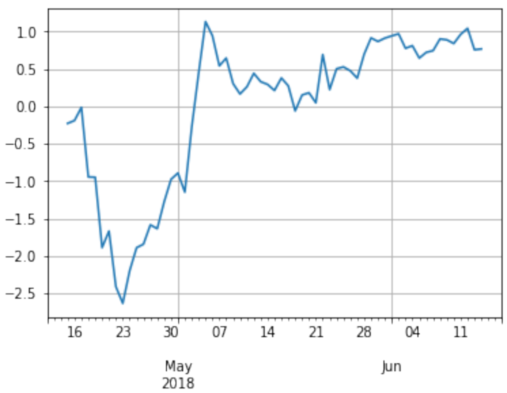
Figure 4: Pairs Z-Score over the spread



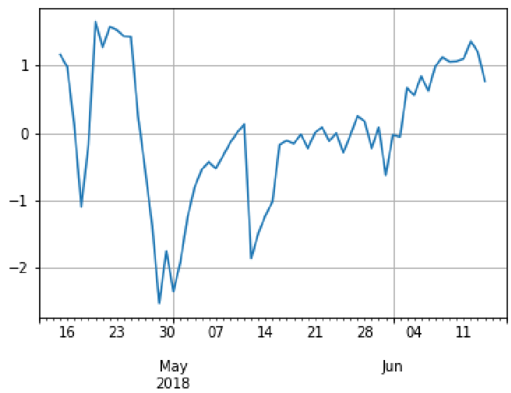
(a) Pair: LSK & ETH



(b) Pair: ICON & LSK



(c) Pair: LTC & XMR

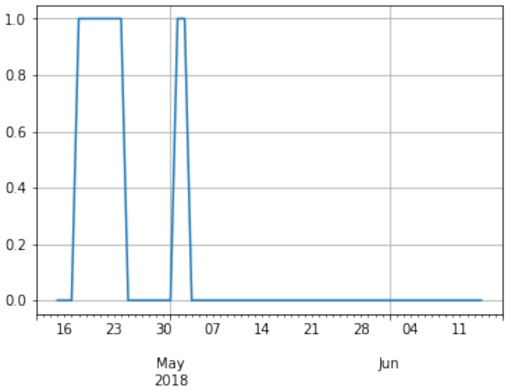


(d) Pair: XRP & XLM

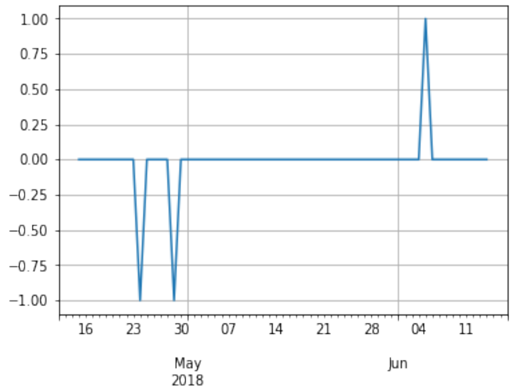
The Y-axis corresponds to the Z-score calculated over the spread during the trading period of 15 April 2018 to 15 June 2018. During this period the cryptocurrency market only provides a handful of trading signals. For example, the pair LTC & XMR only surpasses the 2 historical standard deviations a single time, meaning in 60 days there is 1 single position opened.

In the investigated period all of the four pairs showed only one up to three moments when the required threshold of two standard deviations was reached. Therefore, from the practical point of view, this limits the number of trading actions, which in turn gives fewer opportunities for positive returns. Based on the Z-score, the trading rules can be executed. In Figure 5 the activity of opening a position, either long or short, is illustrated. A positive peak means going long in the first cryptocurrency of the pair (i.e for LSK & ETH, going long in LSK and shorting ETH), contrary, a negative peak means going short in the first cryptocurrency of the pair.

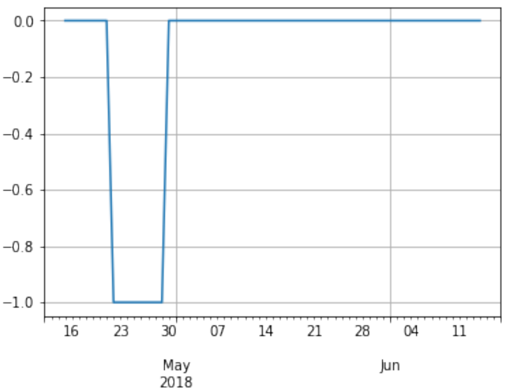
Figure 5: Pairs Trading Strategy



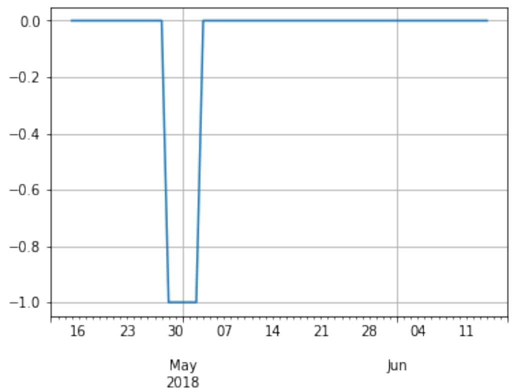
(a) Pair: LSK & ETH



(b) Pair: ICON & LSK



(c) Pair: LTC & XMR

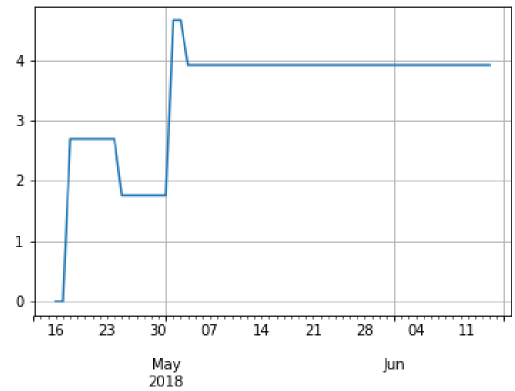


(d) Pair: XRP & XLM

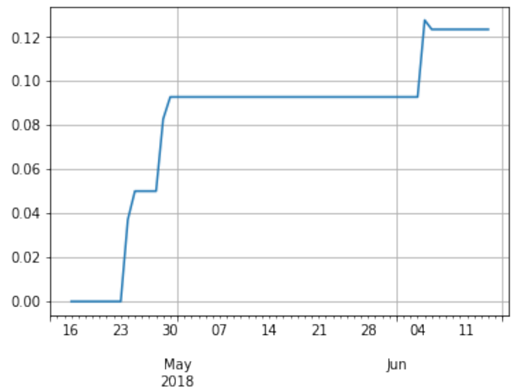
The Pairs Trading Strategy is as follows, 1.0 = long first crypto & short second crypto, −1.0 = short first crypto & long second crypto. The width of spike reflects how fast the position is unwound thus how long it took before the spread starting to converge back to it's equilibrium. All of the pairs converge back, with most of the pairs converging back fairly within a small time-frame (a couple days).

As last, executing the pairs trading strategy displayed in Figure 5 above, the results of the trades are accounted in the MTM pnl. The MTM pnl is illustrated in Figure 6 below.

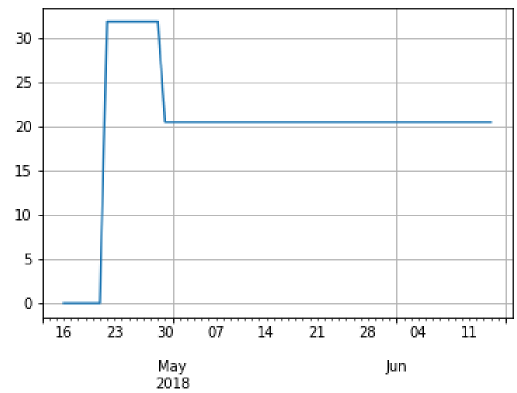
Figure 6: Pairs MTM pnl



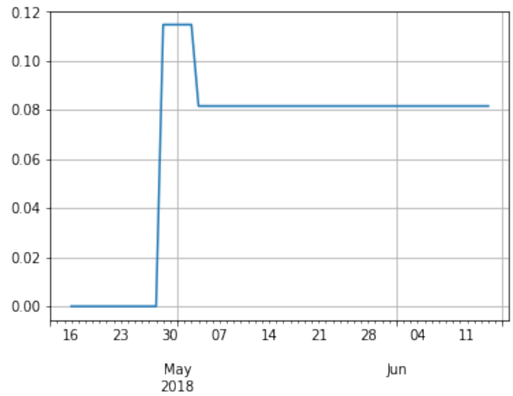
(a) Pair: LSK & ETH



(b) Pair: ICON & LSK



(c) Pair: LTC & XMR



(d) Pair: XRP & XLM

The MTM pnl displays positive results for all four pairs, because, as shown in Figure 5, all pairs at some point converge back after they surpass the 2 historical standard deviations. The returns are denoted in absolute values (in $) of the denominating cryptocurrency of the pair.

As shown in Figure 6 above, applying the pairs trading strategy to the four selected pairs gives positive returns. When a position is opened, the overvalued cryptocurrency (of the pair) is shorted and generates a positive cash inflow greater than the cash outflow from going long in the undervalued cryptocurrency: this can be observed in all the sub-figures. When the position is closed, usually (ICON & LSK as an exception) a decrease in the MTM pnl can be noticed. The sum of the cash outflow for buying the shorted cryptoccurency back and the cash inflow for selling the longed cryptocurrency is negative. However, regardless of this decrease in the MTM pnl, all of the pairs show positive returns. The strategy turns out profitable and the EMH is violated, thus the EMH hypothesis is rejected for the cryptocurrency market.

6 Conclusion

This research examines the possibilities of pairs trading in the cryptocurrency market. It does so by focusing primarily on two sub questions. The first question was as follows:

1. *Are there any cointegrated pairs in the cryptocurrency market?*

The cryptocurrency market has hundreds of different cryptocurrencies. To capture the most relevant ones filters were applied, which resulted in a dataset of 34 coins. Afterwards, the cointegration method of Vidyamurthy (2004) was used, during the period 15 September 2017 to 15 April 2018, to find cointegrated pairs in the data set. A total of 31 pairs were found that showed significant cointegration (sector and cross-sector), confirming that there are cointegrated pairs in the cryptocurrency. After finding cointegrated pairs, this research used a pairs trading strategy to find an answer to the second question:

1. *Does the EMH hold for the cryptocurrency market?*

To test this hypothesis this research applied a simple pairs trading strategy based on the trading rules similar to trading criteria of Gatev et al. (1999). Out of all 31 pairs, arbitrarily, four pairs were selected and tested over a 60-day trading period. The strategy turned out to give positive returns as can be observed in the Trading Period Section. The pairs trading strategy is getting its profitability from arbitrage opportunities in the cryptocurrency markets. Arbitrage opportunities can only exist if the market EMH does not hold. Therefore the hypothesis that the EMH holds for the cryptocurrency market is rejected. This research concludes that the pairs trading strategy can successfully be applied to the cryptocurrency market and profits can be generated.

Limitations

This research is subject to a number of limitations. The first, is neglecting different trading fees and costs for shorting. These costs could significantly decrease the profitability, or even to the point where pairs trading is unprofitable. In the case of unprofitability, the EMH holds.

The second limitation are the trading rules used in this research. Two historical standard deviations might not be the most optimal point to open a position, as well as closing the position at one historical standard deviation.

Finally, the selection of four pairs to test for profitability is arbitrarily. This way of selection can cause a selection bias, and the examined pairs might not represent the average profitability of the pairs trading strategy. Instead, all pairs could be tested for profitability and the aggregated results would show a non-biased picture of the profitability of pairs trading in the cryptocurrency market.

Further Research

This research applies a cointegration based pairs trading framework to the cryptocurrency market. There are different ways to extend on this foundation. In the section above three limitations of this study are given. One could replicate this study and solve the limitations by implementing trading and shorting cost as well as test all pairs for profitability (rather than four).

Also, the stochastic spread method was shortly described, but was out of the scope of this research. A future research could utilize the stochastic spread method to find more optimal trading signals. Since the cryptocurrency market is developing rapidly, the market (i.e relevant alternative cryptocurrencies, the cointegrated relationships between coins) could drastically change within a short time frame. Therefore, performing the same study over a more up-to-date dataset might give different results.

Furthermore, instead of using daily historical prices, hourly or even minutely historical prices can be examined. These hourly or, preferably, minutely historical prices can also be used to evaluate the profitability of high-frequency pairs trading with application to the cryptocurrency market.

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Appendices

A Supplementary Equations

To answer the question why the order of variables for cointegration (via the Engle-Granger) method matters, consider the following simple regression model, which can be used to find the cointegration coefficient β in a case of two variables (such as in this research):

$$\hat{\beta}_{P_i,P_j} = \frac{Cov[P_i, P_j]}{\sigma^2_{P_i}} \tag{A.1}$$

The same regression model, however now P_j is regressed on P_i:

$$\hat{\beta}_{P_j,P_i} = \frac{Cov[P_j, P_i]}{\sigma^2_{P_j}} \tag{A.2}$$

It is clear that $Cov[P_i, P_j] = Cov[P_j, P_i]$, however generally $\sigma^2_{P_i} \neq \sigma^2_{P_j}$, therefore $\hat{\beta}_{P_i,P_j}$ is not a scalar multiple of $\hat{\beta}_{P_j,P_i}$. Hence, the residuals series, or spread series, used in the second step of the Engle-Granger 2-Step method to test for a unit root are not scalar multiples of each other:

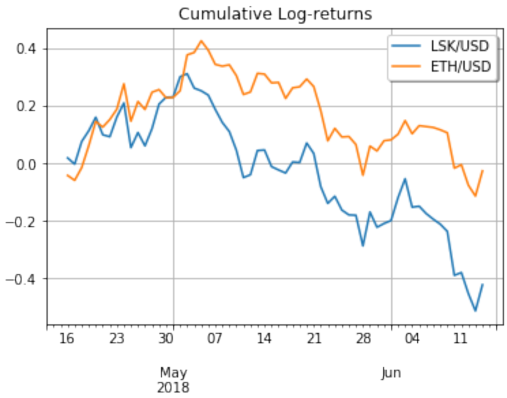
$$u^1_t = P_{it} - \beta^1 P_{jt} \tag{A.3}$$

$$u^2_t = P_{jt} - \beta^2 P_{it} \tag{A.4}$$

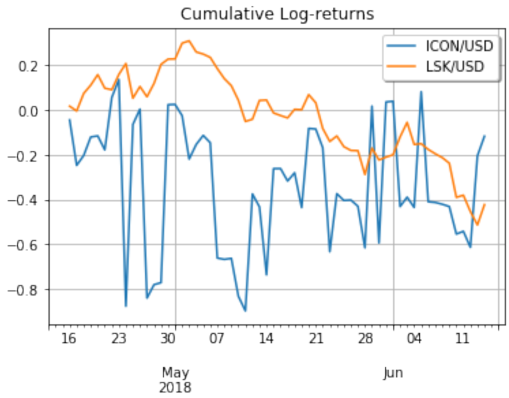
In general, $\beta^1 \neq a * \beta^2$ for some scalar a. Therefore, both orientations are tested in the form of permutations.

B Supplementary Figures

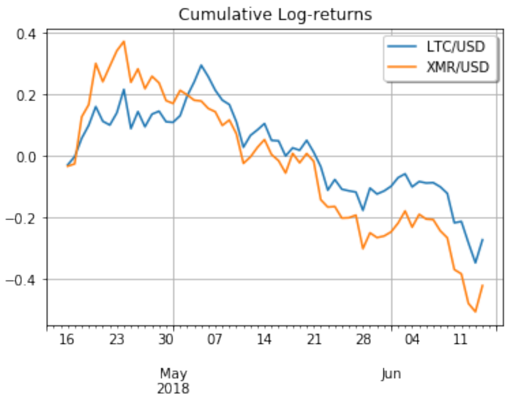
Figure B.1: Pairs Cumulative Log-Returns



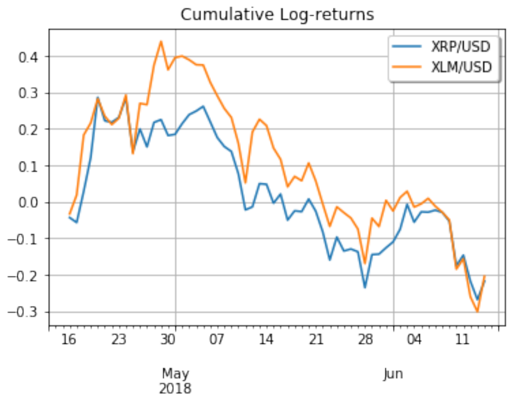
(a) Pair: LSK & ETH



(b) Pair: ICON & LSK



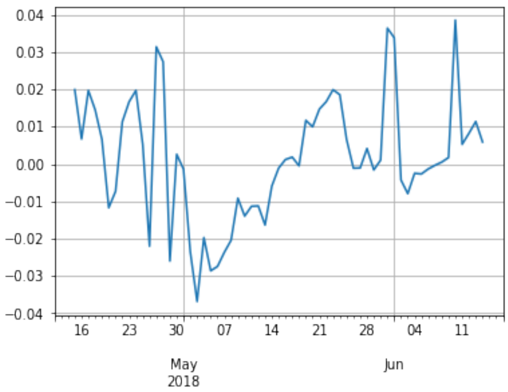
(c) Pair: LTC & XMR



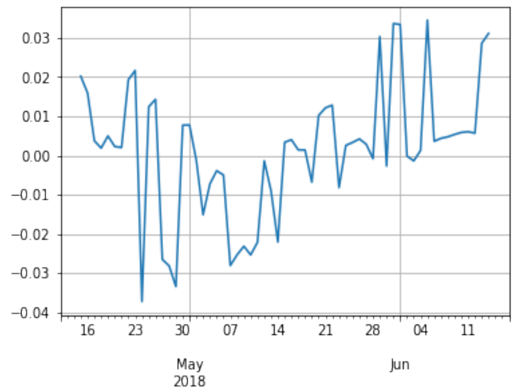
(d) Pair: XRP & XLM

Cumulative log-returns for all four pairs. The cryptocurrency market experienced a downtrend during the trading period of 15 April 2018 - 15 June 2018.

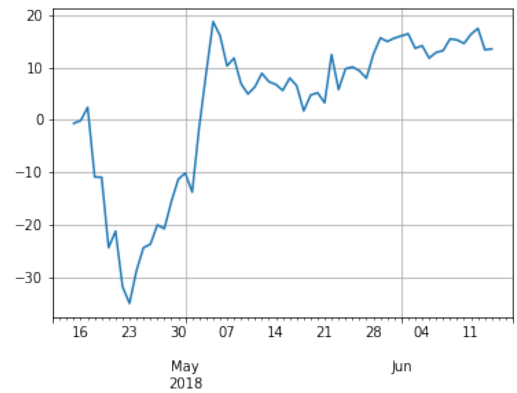
Figure B.2: Pairs Spread



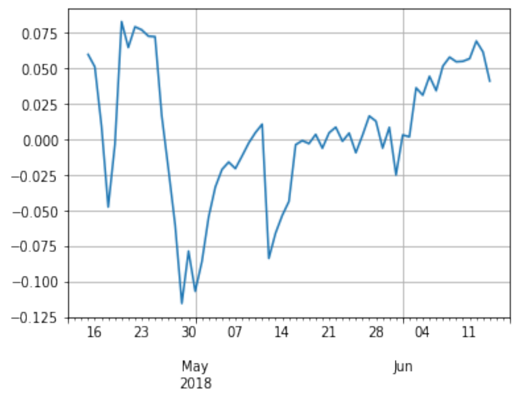
(a) Pair: LSK & ETH



(b) Pair: ICON & LSK



(c) Pair: LTC & XMR



(d) Pair: XRP & XLM

The spread for all pairs. The pairs LSK & ETH and ICON & LSK show bigger spikes compared to LTC & XMR and XRP & XLM. The spikes reflect higher volatility in the spread, which leads to more trading signals (see Figure 5).

C Supplementary Tables

Table C.1: Cryptocurrency Dataset Overview

Coin name	Coin Symbol	Market Capitalization	Price	Volume (last 24 hr)
Bitcoin	BTC	$137.457.941.053	$8.096,05	$5.037.283.036
Ethereum	ETH	$50.534.138.957	$511,33	$1.572.430.005
Ripple	XRP	$25.232.558.148	$0,644958	$562.988.674
Bitcoin Cash	BCH	$12.855.471.206	$752,92	$275.750.889
Litecoin	LTC	$7.188.358.061	$128,16	$246.867.468
EOS	EOS	$6.544.301.145	$8,24	$1.118.649.168
Cardano	ADA	$5.366.760.737	$0,206994	$104.493.841
Stellar	XLM	$4.882.626.603	$0,263077	$49.732.367
NEO	NEO	$4.263.830.565	$65,60	$87.027.002
IOTA	MIOTA	$4.251.403.064	$1,53	$65.113.312
Monero	XMR	$3.093.717.260	$194,20	$45.392.845
Dash	DASH	$2.929.051.042	$365,64	$79.798.640
NEM	XEM	$2.856.723.301	$0,317414	$38.587.765
TRON	TRX	$2.680.713.015	$0,040772	$271.435.571
VeChain	VEN	$1.763.469.847	$3,35	$69.008.915
Ethereum Classic	ETC	$1.644.234.157	$16,25	$125.279.218
Binance Coin	BNB	$1.543.868.927	$13,30	$88.460.791
Qtum	QTUM	$1.430.991.645	$16,17	$175.023.333
OmiseGO	OMG	$1.422.491.292	$13,94	$72.086.794
Verge	XVG	$1.337.254.453	$0,089886	$156.859.246
Lisk	LSK	$1.052.180.699	$10,13	$15.196.673
ICON	ICX	$976.291.637	$2,52	$25.894.155
Bytom	BTM	$886.516.888	$0,898193	$71.407.468
Zcash	ZEC	$836.787.563	$225,89	$51.625.430
Nano	NANO	$798.352.096	$5,99	$13.151.658
Wanchain	WAN	$627.554.833	$5,91	$27.437.632
Siacoin	SC	$580.772.271	$0,017187	$43.503.582
BitShares	BTS	$537.303.502	$0,205394	$24.794.195
Ontology	ONT	$513.001.593	$4,56	$61.529.660
Dogecoin	DOGE	$479.714.715	$0,004207	$11.679.983
Waves	WAVES	$477.471.859	$4,77	$27.099.378
Zilliqa	ZIL	$430.214.473	$0,059063	$15.151.308
Decred	DCR	$428.972.446	$60,16	$15.612.266
Gas	GAS	$193.225.891	$19,15	$4.119.048

Table C.2: Dataset by sector

Sector	Market Capitalization	Percentage of Total
Application Platform	$75,375,680,327.00	26.16%
Financial Transactions	$193,575,397,392.00	67.19%
Private Digital Currency	$8,196,810,318.00	2.85%
Other	$10,950,376,907.00	3.80%
Total Dataset	$288,098,264,944.00	89.12%
Total Market	$323,287,382,648.00	100%

The dataset represents 89.12% of the total cryptocurrency market market capitalization, with the financial transactions sector providing the majority of the value (Within the financial sector Bitcoin dominates).

Table C.3: Sector Grouping

Application Platform	Financial Transactions	Private Digital Currency	Other
Ethereum / ETH	Bitcoin / BTC	Monero / XMR	Zilliqa / ZIL
EOS / EOS	Stellar / XLM	Dash / DASH	Binance Coin / BNB
Cardano / ADA	Bitcoin Cash / BCH	Verge / XVG	OmiseGO / OMG
NEO / NEO	Litecoin / LTC	Zcash / ZEC	Waves / WAVES
NEM / NEM	Ripple / XRP		Bytom / BTM
Ethereum Classic / ETC	IOTA / IOT		VeChain / VEN
QTUM / QTUM	Nano / NAN		Wanchain / WAN
Lisk / LSK	Dogecoin / DOGE		Tronix / TRX
Iconic / ICON	Decred / DCR		Siacoin / SC
Ontology / ONT			Bitshares / BTS
Gas / GAS			

Table C.4: Engle-Granger 2-Step results for the Application Sector

Application Sector	Cryptocurrencies*	T-Statistic	P-statistic**
	ICON & LSK	-4.4663	0.0014
	ICON & ETH	-4.2860	0.0027
	ADA & EOS	-4.0421	0.0062
	ICON & NEO	-3.6749	0.0197
	ICON & GAS	-3.6733	0.0198
	ICON & EOS	-3.6064	0.0241
	LSK & ETH	-3.4063	0.0417

* Cointegrated pairs

**The Engle-Granger 2-Step test with a minimum of 5% significance level

Table C.5: Engle-Granger 2-Step results for the Financial Sector

Financial Sector	Cryptocurrencies	T-Statistic	P-statistic*
	XRP & XLM	-3.7372	0.0164
	BTC & BCH	-3.5294	0.0299

*The Engle-Granger 2-Step test with a minimum of 5% significance level

Table C.6: Engle-Granger 2-Step results for the Application & Financial Sector

Application & Financial Sector	Cryptocurrencies	T-Statistic	P-statistic*
	DOGE & QTUM	-3.8419	0.0119
	ICON & XRP	-3.6049	0.0242
	QTUM & DOGE	-3.5938	0.0249
	ADA & XRP	-3.5752	0.0263
	DOGE & EOS	-3.5503	0.0282
	XRP & ADA	-3.5351	0.0294
	BTC & BCH	-3.5294	0.0299
	ICON & DOGE	-3.5015	0.0323
	LTC & QTUM	-3.3546	0.0477

*The Engle-Granger 2-Step test with a minimum of 5% significance level

Table C.7: Engle-Granger 2-Step results for the Financial & Private Sector

Financial & Private Sector	Cryptocurrencies	T-Statistic	P-statistic*
	LTC & XMR	-4.0248	0.0066
	XMR & LTC	-3.5432	0.0288
	DOGE & XMR	-3.3379	0.0498

*The Engle-Granger 2-Step test with a minimum of 5% significance level

Table C.8: Engle-Granger 2-Step results for the Application & Private and Other Sector

Application & Private & Other	Cryptocurencies	T-Statistic	P-statistic*
	OMG & EOS	-4.3536	0.0021
	ICON & OMG	-3.8929	0.0101
	OMG & ETH	-3.7514	0.0157
	EOS & OMG	-3.6196	0.0232
	TRX & XVG	-3.5575	0.0276
	TRX & EOS	-3.5239	0.0303
	TRX & QTUM	-3.5080	0.0317
	QTUM & XMR	-3.4801	0.0342
	OMG & LSK	-3.4483	0.0373
	ICON & XMR	-3.3614	0.0468

*The Engle-Granger 2-Step test with a minimum of 5% significance level