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Pairs Trading in the Cryptocurrency Market: An Empirical Analysis of Trading Signals and Performance Metrics

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ABSTRACT

This dissertation studied whether performing a pairs trading strategy yields positive excess returns in the market of cryptocurrencies. The profitability of this strategy was evaluated by performing a backtest using the top 30 cryptocurrency pairs. These pairs were formed by means of the correlation method using the closing price data of 50 cryptocurrencies over a 3-year period. It can be observed that executing this method yields significant abnormal returns of 12% per month. This finding exceeds conservative transaction cost estimates and the strategy tends to be successful in periods of crisis. With no evidence being found of decreasing efficacy of pairs trading, the strategy proves to be a consistent method of statistical arbitrage which can be used worldwide by investment banks, hedgefunds or even individual investors.

Keywords: Pairs trading, correlation method, cryptocurrencies, statistical arbitrage

JEL codes: G11, G12, G14, G17

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 Introduction

Cryptocurrencies have been a hot topic in the recent years, especially in the year 2021 following the covid-19 crisis. The crypto market acknowledged an all-time high and almost every single person knows of its existence. This is why it is not surprising that more and more traders find ways to make profit from this trend. Cryptocurrencies are some form of electronic money that is designed to act as a medium of exchange through a computer network, without having to rely on any central authority. It was first introduced by the American cryptographer David Chaum (1981). This digital currency was untraceable by a third party because it required specific encrypted keys. Cryptocurrencies became known to the public when a paper about Bitcoin was published by Nakamoto (2008), which resulted in its birth the following year. Now that cryptocurrencies are introduced to the financial markets, it is important to determine whether there is a trading strategy that obtains positive abnormal returns using this asset class. One of the most exciting statistical arbitrage tools in the equity market used by investment banks and hedge funds is the pairs trading strategy. But is it possible to combine these two subjects and find a pairs trading strategy which leads to positive abnormal returns in the cryptocurrency market?

Pairs trading has been a well-researched topic with its most famous publication being released by Gatev et al. (2006). In this paper they came to the conclusion that pairs trading is a profitable trading strategy with an average annualized excess return of 11%. Pairs trading is a strategy that involves matching a short position with a long position in two stocks with a high correlation. Due to divergence and convergences of the prices, profit can be made. It is interesting to know how to profitability of pairs trading has developed over the years. Do and Faff (2010) came to the conclusion that the strategy still obtains positive excess returns. They also came to the conclusion that it performs better during financial crisis, which is consistent with Gatev et al (2006) finding that pairs trading performs better when the stock market performs poorly. The link between pairs trading and cryptocurrencies was researched by Kristoufek et Fil (2020), where they found that this strategy can perform well under certain conditions. But, they admit that the strategy strongly underperforms previous benchmark literature. Another research was conducted by Saji (2021) where the same relation was studied, but with a couple of major differences. For instance, this paper looked only at the top 4 cryptocurrencies instead of 26. The results of the paper showed that trading with suitably formed pairs of cryptocurrency displays profits exceeding the conservative profit estimates of portfolio management.

In this paper there will be examined whether pairs trading can be applied to the cryptocurrency market and if positive excess returns can be observed. From the efficient market hypothesis and traditional economic theory, we know that markets will not show abnormal returns if they were efficient at all times (Malkiel 2003). It is thus important to determine first whether the cryptocurrency market is efficient or not. Bouri et al. (2018) and Cagli (2019) provided evidence for the non-efficiency of crypto markets. These results suggest that abnormal returns can be obtained in the cryptocurrency market thus making it interesting to look at any exploitable trading strategies, in particular the previously mentioned pairs trading strategy. The following research question will be formed: "Does pairs trading in cryptocurrency markets still display positive excess returns?" Kristoufek et Fil (2020) and Saji (2021) show that this can be concluded to be true. However, these papers have used a relatively small sample size and a brief time period which limits the robustness of the results. To account for this, this study will make adjustments to improve the validity of the results.

The data used in this thesis originates from Yahoo Finance and is publicly available online. This study will look at the top 50 cryptocurrencies ranked through market capitalization over a period of 3 years [01-01-2020, 31-12-2022]. I have chosen this interval to also account for covid-19 so that we can observe the effects of crisis and uncertainty on our trading strategy. There are no closing days to take into account since cryptocurrencies are exchanged continuously. Therefore, the prices in the research will reflect the 24-hour price change, where prices are indicated in US dollars. For this study I will conduct a quantitative analysis in the form of back testing, inspired by Gatev et al. (2006). I will use historical price data to identify pairs of cryptocurrencies that are suitable for trading and backtest the trading strategy over a period of 3 years. The backtesting involves simulating the execution of trades based on the trading signals generated by the strategy and calculating the profit or loss of the strategy over time. If the spread between the pair widens by more than 1.5 times the standard deviation, a long-short position will be opened for the lowest- and highest priced crypto, respectively. The position will be closed when the prices revert. Cryptocurrenciy pairs can be formed in a variety of ways (Blasquez et al. 2018). Most researchers use either the distance method or the cointegration method. To make matters more interesting, this paper will use the correlation method used by Ehrman (2006) and Wong (2010). This technique chooses pairs of an asset class according to the Pearson correlation coefficient between them. Each crypto can only have one pair and these pairs require a minimal correlation coefficient of 0.8 to ensure a strong relationship.

Based on Kristoufek et Fil (2020) and Saji (2021) I expect that this research will display positive excess returns when implementing the pairs trading strategy in crypto markets. In addition, I expect that this strategy performs better during the covid-19 crisis than under normal circumstances. I expect to obtain more robust results than previous literature studying the same phenomenon, since we are taking into account the top 50 cryptocurrencies as well as observing a 3-year time interval. Finally, I expect that even though our trading strategy displays positive excess returns, it will still underperform pairs trading in benchmark literature due to the decreasing trend in profitability.

CHAPTER 2 Theoretical Framework

2.1 Concept

Pairs trading is a trading strategy that enables traders to make profit from market movements. It is a relatively simple concept, where you find two stocks whose prices have moved together historically. The moment that the price of these stocks diverges you short the overperforming asset and you buy the underperforming one. If history repeats itself, the prices will converge back together and you have made profit. This convergence of prices relies heavily on cointegration. It refers to the statistical relationship between two time series that have a long-term equilibrium relationship, which results in deviations to be temporary. The pairs trading strategy is categorized as a market-neutral strategy, which aims to minimize exposure to systematic or market-wide risk factors. Instead, it relies on the relative movements of two specific securities, which can be useful in volatile or uncertain market conditions. In addition, pairs trading can be used to hedge against specific risks, such as industry or sector-specific risks, while still allowing the trader to benefit from the overall movement of the market. This is why it is no surprise that the pairs trading strategy is among the statistical arbitrage tools used by hedge funds as well as investment banks (Kanamura et al. 2008).

2.1.1 History

Pairs trading was first introduced by Gerry Bamberger and it was followed up by Nunzio Tartaglia with the help of an assembled team at Morgan Stanley in the 1980's (Yang et al. 2016). With this strategy they replaced the trader's skill with consistent filter rules to exploit existing arbitrage by identifying pairs whose price moved together. They performed well with this strategy in the year 1987 when they reportedly made a 50 million profit for the enterprise. Dr. Aaron Brown played a significant role in advancing pairs trading. In the mid-1990s, Brown joined Morgan Stanley and contributed to refining and enhancing the strategy. He introduced statistical tools, risk management techniques, and position-sizing methodologies, making pairs trading more robust and profitable. Technological advancements also played a crucial role in the growth of pairs trading. The availability of computational power and historical financial data facilitated the development of sophisticated quantitative models and algorithms. These tools enabled traders to identify and execute pairs trading opportunities more efficiently. The strategy became increasingly more popular and had its first big academic breakthrough following research conducted by Gatev et al. (2006), which showed that pairs trading consistently yields positive excess returns.

2.2 Foundation

One could believe that pairs trading is simply a form of mean-reversion, which is a concept used to explain the eventual reversion of asset price volatility and historical returns to a long-run mean value. This mean-reversion behaviour was observed by Fama and French (1988) and later turned into a trading strategy by Jegadeesh and Titman (1993) where one massively buys assets that have fallen below its historical average (losers) and sells assets that have risen above their mean value (winners). However, Gatev et al (2006). showed that the pairs trading returns exceed the formerly studied mean reversion effect. They did this by bootstrapping randomly formed pairs, which failed to display positive excess returns proving that the pairs trading effect is different than mean-reversion. In addition, the authors ruled out several other explanations for the pairs trading profits, Including transaction cost and unrealized bankruptcy risk.

Gatev et al. (2006) observed a downward trend in the probability of pairs trading and came up with a possible explanation for this phenomenon, stating that the increase in the strategy's popularity led to more competition and decreased opportunity. This downward sloping trend was examined by Do and Faff (2010). The authors studied whether pairs trading was still a profitable trading strategy and came to the conclusion that this was indeed the case, but in a lesser extent and in a decreasing manner. In this paper they also came to the conclusion that the strategy performs better during financial crisis, which was in line with the results of Gatev et al. (2006) finding that pairs trading is more profitable when the stock market performs poorly. This can be linked to the fact that pairs trading strategies are generally more effective in highly volatile markets, where there will be bigger price fluctuations due to the high volatility within the assets of a pair (Rad et al 2016). Volatile assets are characterized by significant price movements, presenting more frequent opportunities for deviations from their normal price relationship. Do and Faff (2012) also examined in another article whether pairs trading profits are robust to trading cost and found that the strategy remains profitable after controlling for commissions, market impact and short-selling fees.

A possible psychological explanation for pairs trading profits is that human beings do not like to go against human nature. One wants to buy financial assets when they go up in price not down (Hansel 1989). Meaning that pairs trading profits can be obtained as a result of the discipline of investors, who are taking advantage of the undisciplined overreaction displayed by individual investors. This finding is in line with the discovery of Jegadeesh and Titman (1995) that contrarian gains are partially a result of an overreaction to company-specific information shocks as opposed to price reactions to common factors. According to Andrade et al. (2015), uninformed buying is the dominant factor behind spread divergence. They state that pairs returns are highly corelated with uninformed demand shocks in the underlying asset and conclude that pairs trading profits are a compensation for liquidity provision to uninformed buyers. Papadakis et Wysocki (2007) find that pairs trades are often opened around analyst forecasts and earnings announcements. Trades triggered after such events are significantly less profitable than those in non-event periods, which can be explained by investor underreaction.

Besides the stock market, pairs trading has been proven to be a profitable trading strategy in other financial markets. For instance, Ungever (2015) provided evidence for positive excess returns in the commodities market and Hodges et al. (2013) displayed proof of pairs trading as a profitable trading strategy in the foreign exchange market. An efficient market should not contain these exploitable trading strategies where positive excess returns can be made through mispricing. This phenomenon is called the efficient market hypothesis (EMH), which states that prices reflect all information. This theory was introduced by Fama (1970) and is to this day widely accepted by academics and modern investors. Malkiel (2003) thoroughly examined the EMH and concluded that the theory is still relevant. However, he also acknowledged the need for ongoing research and refinement of the theory.

2.3 Pairs trading in crypto markets

Cagli (2019) and Bouri et al. (2018) provided evidence for the non-efficiency of crypto markets. The EMH does not hold in this market, which means that pair trading strategies are expected to yield abnormal excess returns. In addition, cryptocurrency markets are also known to be sensitive to bubbles, which results in frequent bear markets (Corbet et al. 2018). In a bear market where prices keep falling for a sustained period of time, it can generally be quite tricky to experience success while trading. However, from Gatev et al (2006) we know that pairs trading strategies are more successful when stock markets perform poorly. Dyhrberg (2016) provides evidence for high liquidity in cryptocurrency markets, particularly the Bitcoin. High liquidity in crypto markets is generally considered beneficial for pairs trading strategies. When a market is highly liquid, there are more buyers and sellers and trading can occur quickly and at lower transaction costs. This can lead to more efficient prices and less transaction cost, meaning higher trading profits.

Prior research conducted by Fil et Kirstoufek (2020) tested whether the pairs trading strategy is profitable in crypto markets. They did this by filtering 181 cryptocurrencies on Binance, which results in them eventually using 26 cryptocurrencies. For these currencies they look at the daily, hourly and monthly frequencies, using a time interval of Jan 2018 to Sept 2019. In this paper they use the cointegration method and the distance method to form pairs. The two methods are backtested using various sampling frequencies and a parameter sensitivity analysis is also carried out. They found that the trading strategy in this market can perform well under certain conditions, especially with higher frequency trading. However, they admit that the strategy strongly underperforms previous benchmark literature. A possible explanation for these findings is that the common belief of the high predictability of cryptocurrency is wrong. In addition, they argue that building a trading strategy is rather difficult in an inefficient market. An upcoming concept in the field of pairs trading in cryptocurrencies is the use of machine learning. Machine learning is a subset of artificial intelligence that involves using algorithms to automatically learn patterns and relationships from large datasets, and then use that learning to make predictions or decisions. Fischer et al. (2019) explores the use of advanced machine learning techniques, such as random forests, in the field of pairs trading in cryptocurrency markets. The authors found evidence for both economically and statistically significant excess returns, but under the condition of adequate timing. Even though, it can be interesting to dive deeper into machine learning, for this paper the traditional approach will be used. This is due to the fact that there is far more relevant literature following this approach.

Another research following the classic pairs trading approach was conducted by Saji (2021) where they looked at the daily prices of 4 arbitrarily chosen cryptocurrencies. They examined a 2-year timespan, divided into four sub-samples (6 months each). This paper makes use of the cointegration method. After the pairs have been formed based on cointegration, the data is backtested. The author came to the finding that trading with suitably formed pairs of cryptocurrency displays profits, which are superior to conservative profit estimates of portfolio management. The findings show that the long-short strategy of pairs trading consistently beats the general buy-hold strategy of investing in cryptocurrency markets.

Based on the reviewed empirical literature about this topic, executing pairs trading strategies on cryptocurrencies will consistently yield significant profits exceeding the market. Therefore, the following hypothesis can be formulated:

H1: *Pairs trading in cryptocurrency markets display positive excess returns*

CHAPTER 3 Data

For this study, the historical price data was collected on the 50 highest-ranked cryptocurrencies (through market capitalisation) for the period between January 1, 2020 and December 31, 2022. All the price data series are in US Dollar terms. The data was retracted from Yahoo Finance, using a daily frequency. Out of the initial 50 cryptocurrencies, 17 were carefully filtered out to ensure the reliability and quality of the data set. This process aimed to eliminate any outliers or inconsistencies that could potentially impact the accuracy of the results obtained. Examples of filtered-out currencies are those that were only introduced to the market in the latter stages of our time interval or those with missing data points. After the pre-processing, the data will consist of a final set of 33 cryptocurrencies.

From the final dataset can be observed that it consists of so-called ”stablecoins”. Stablecoins are cryptocurrencies which are designed to have relatively stable prices, typically through being pegged to some external references, such as currencies or commodities. The stablecoins in our sample are pegged to the US Dollar as the price of the coins are fixed at around 1 USD. Within our data, these coins are: USDT, USDC, BUSD, DAI, TUSD and USDP as can be observed from Table 1. Stablecoins can act as a hedging tool to mitigate the risks associated with other volatile assets in your portfolio. By pairing a stablecoin with a volatile asset, you can potentially reduce the overall risk exposure and stabilize your returns. Stablecoins also often have high liquidity, which means they can be easily traded for other cryptocurrencies or assets. This liquidity can facilitate faster execution of your pairs trading strategy. However, it is important to consider that stablecoins are designed to minimize price fluctuations. This goes against the nature of pairs trading which relies on price fluctuations and is more successful when applied to volatile assets. Due to this ambiguity, it can be interesting to examine the role of these coins in pairs trading strategies.

The historical price data consist of the following: Date, open, high, low, close, adjusted close and volume. The low price can represent a support level, indicating a point where buying pressure historically prevented the price from falling further. Conversely, the high price can indicate a resistance level, where selling pressure historically prevented the price from rising above a certain threshold. These levels can be significant for technical analysis and decision-making in trading strategies. The volume provides information about the liquidity of the assets traded within a pair and can be used as an additional indicator to confirm trading signals. For example, if a price divergence between the pair is accompanied by higher volume, it may indicate a more reliable trading opportunity and strong buying and selling pressure (Charles et al. 2000)

The main variable of interest from the historical price data is the closing price. These are normally so important because they are used to calculate the returns of a single asset. However, for this study the importance of this variable lies in the fact that the daily closing prices between two cryptocurrencies within a pair will be used to calculate the spread between them. When the spread exceeds a certain threshold, possible trading opportunities can be evaluated by comparing the spread to historical relative prices.

Table 1
Descriptive statistics for the closing prices of the 33 cryptocurrencies left.

Crypto	Obs	Mean	Std. dev.	Min	Max
BTC	1096	28900.78	17117.49	4970.788	67566.83
ETH	1096	1689.834	1272.036	110.6059	4812.087
USDT	1096	1.00059	.0026562	.974248	1.053585
BNB	1096	241.1442	189.5634	9.38605	675.6841
USDC	1096	1.000752	.0042017	.970124	1.044029
XRP	1096	.5462077	.3429052	.139635	1.839236
ADA	1096	.7423736	.7047035	.023961	2.968239
DOGE	1096	.1017124	.1120635	.001537	.684777
MATIC	1096	.7221473	.696091	.008096	2.876757
LTC	1096	107.3582	65.87976	30.93088	386.4508
TRX	1096	.055066	.0308654	.008792	.16465
BUSD	1096	1.000337	.002621	.970006	1.052356
HEX	1096	.0754887	.1021435	.000054	.486741
DAI	1096	1.00278	.0075858	.964845	1.092951
WBTC	1096	28887.75	17090.33	4946.043	67549.23
LINK	1096	14.79509	10.1701	1.741144	52.1987
LEO	1096	2.877902	1.670609	.81996	7.500967
ATOM	1096	14.11444	10.55666	1.649203	44.54279
XMR	1096	165.8377	80.56646	33.01032	483.5836
OKB	1096	13.69451	7.857462	2.548617	42.36211
ETC	1096	25.28356	20.6826	3.963946	134.1018
XLM	1096	.1967948	.1393934	.033441	.729996
BCH	1096	357.9024	218.9768	89.35179	1542.425
TUSD	1096	1.000342	.0026053	.970897	1.044172
FIL	1096	31.94414	35.85007	2.427774	191.3566
HBAR	1096	.1378047	.1190624	.01008	.505923
CRO	1096	.1770914	.1466716	.03007	.900518
BTCB	1096	28863.48	17099.42	4936.755	67502.42
VET	1096	.0497941	.049023	.002274	.254632
QNT	1096	82.7413	83.49142	1.552096	393.5371
ALGO	1096	.6929369	.5229824	.126471	2.37948
USDP	1096	1.000188	.0030545	.970775	1.048037
FTM	1096	.5482075	.7612607	.002288	3.300823

Note. Descriptive statistics of the closing prices of the 33 cryptocurrencies left using daily frequencies between January 1, 2020 and December 31, 2022. From left to right the following data about the closing prices can be observed with respect to each individual cryptocurrency: Number of observations, mean closing price, standard deviation of the closing prices, the minimum – and maximum closing prices.

CHAPTER 4 Methodology

In order to backtest the dataset, the strategy will be divided into two stages. First, the cryptocurrencies will be analyzed over a 6-month period and will be given an adequate partner so that pairs can be formed (formation period). Subsequently, the pairs will be traded in the following 6 months according to certain trading rules (trading period). This entire process will be repeated a total of three times, which results in a trading analysis over a 3-year period.

Table 2:
Overview of the formation- and trading intervals

Number of interval cycle	Formation period	Trading period
1st	January 1, 2020 – July 1, 2020	July 2, 2020 – December 31, 2020
2nd	January 1, 2021 – July 1, 2021	July 2, 2021 – December 31, 2021
3rd	January 1, 2022 – July 1, 2022	July 2, 2022 – December 31, 2022

Note. The table provides information about the dates and lengths of the different formation and trading periods. It can be observed that a formation period is followed up by a trading period. After this process has been completed, the cycle begins again.

4.1 Formation period

As mentioned before, pairs can be formed in a variety of ways. With the most famous methods being the cointegration method and distance method. It is important to briefly discuss these methods before going to the correlation method which is used in this study. This is due to the fact that benchmark literature mostly follows these methods. In addition, the discussion of these methods will give us a deeper understanding of pairs trading.

4.1.1 Cointegration

The most important concept, which all three methods have in common is cointegration between the assets. It is crucial that pairs are cointegrated. If a pair is not cointegrated, the price spread may not revert to its mean and could even diverge further which can result in huge losses. To minimize the chances of this happening, the cryptocurrencies shall first be tested for cointegration. After it can be concluded that there is cointegration between our two assets, a pair can be formed. Cointegration can be tested by using an Engle-Granger test. This test arbitrarily chooses one asset to be the independent variable (Xt) and the other asset as the dependent variable (Yt). The reason for this arbitrary choice is that in the case of pairs trading, it is not needed to determine which asset is the dependent or independent variable. Both assets are treated as potential drivers of the long-run relationship as the test aims to determine if they move together in the long run, regardless of which one influences the other. Additional verification of the arbitrary choice of (in)dependent variables is provided in Appendix A, where the same Engle-Granger test was performed with the only difference being the choice between the independent and dependent variable. By this process can be observed that the choice does indeed not impact the formation results.

With the help of this regression the residuals can then be calculated. The regression equation will have the following form:

$$Y(t) = \alpha + \beta^{*}X(t) + \varepsilon(t) \tag{1}$$

The regression model will then be used to calculate the residuals by subtracting the fitted values ($\alpha + \beta^{*}X(t)$) from the actual values ($Y(t)$). Then, an Augmented Dickey-Fuller test will be used on the residuals obtained from the regression to check for stationarity. If the residuals are stationary, then the two asset prices are cointegrated (Engle & Granger 1987).

It is crucial to know the difference between cointegration and correlation. Correlation measures the strength of a linear relationship between two variables and what direction these tend to move. It explains how the changes in one variable correspond to the other, without necessarily implying a causal or long-term relationship. In addition, correlation does not require the variables to be stationary. On the other hand, cointegration refers to a long-term relationship between variables, indicating that they move together in the long run despite potentially exhibiting short-term deviations. Cointegration implies a stable equilibrium or a shared trend between the variables and it requires the variables to be non-stationary individually, but to possess a stationary linear combination.

4.1.2 Different techniques

Now that cointegration has been ascertained, the pairs can be formed. As mentioned previously, this formation can be done in a variety of ways. The cointegration method was introduced to pairs trading by Vidyamurthy (2004). This method chooses pairs based on the cointegration coefficients and is still one of the most popular techniques used today.

Another popular method is the distance method used by Gatev et al. (2006). It chooses the pairs based on the distance between them, which is calculated as the sum of the squares of the differences between the standardized prices of the two assets. Pairs will then be picked based on the combinations that minimize this metric:

$$D_{ij} = \sum_{t} (P_{it} - P_{jt})^2 \tag{2}$$

The method that will be used in this study is the correlation method. This method was used by Ehrman (2006) and Wong (2010). As the name suggests, this technique chooses pairs based on the Pearson correlation coefficient between assets. The cryptocurrencies with the highest correlation between them will be formed into a pair. Note that each crypto can only form 1 pair each interval to limit excessive exposure of a cryptocurrency, since a market-neutral investing strategy's primary objective is to lower investment risk. In addition, a pair requires a minimum correlation coefficient of 0.8 to ensure a strong relationship. Lastly. stablecoins and coins which are very similar to one another are taken into account while forming pairs. For example, TUSD and USDP will never be formed into a pair since they are two stablecoins (Even if they meet the requirements for pairing). This is due to the fact that a pair of stablecoins will display minimal spread, which limits our trading strategy. However, it is possible for a stablecoin to form a pair with a non-stablecoin. The same applies to cryptocurrencies that are backed 1 to 1 by another, such as BTC and WBTC

4.2 Trading period

On the day following the formation period, the cryptocurrencies can be traded according to prespecified rules. The trading rules are selected based on the concept that a long–short position is opened when the pair prices have diverged by a certain amount and the position closes again when the prices have reverted. The rules for opening and closing positions is based on a standard deviation metric. A position in a pair is opened when prices diverge by more than 1.5 historic standard deviations, as estimated during the pairs formation period. The position is closed at the next crossing of the prices, so when they convert back together. If prices do not cross, gains or losses are calculated at the end of the trading interval. The payoffs are reported by going one dollar long in the underpriced cryptocurrency and one dollar short in the overpriced cryptocurrency.

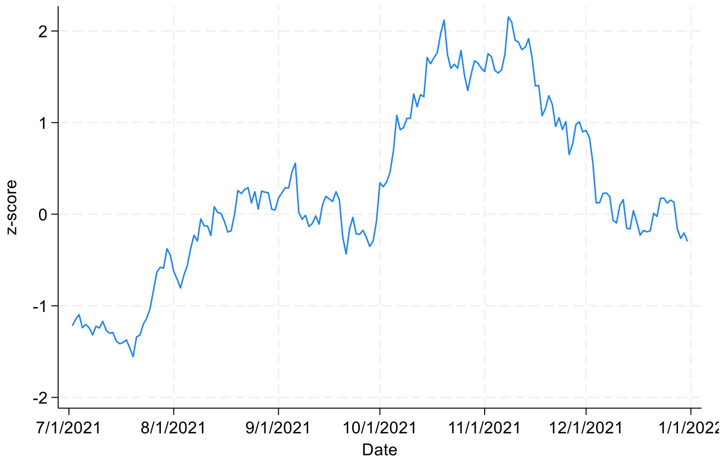
The trading rules will be applied with the use of z-scores (see below). Since, we are using a 1.5 historic standard deviation metric. The position will be opened at a z-score of 1.5/-1.5 and the position will be closed if the z-score crosses 0. The mean used for this computation is a moving average or rolling mean due to its ability to better capture short-term trends and mean reversion opportunities, which pairs trading strategies wish to exploit. In addition, a moving average helps smoothing out random fluctuations. By doing so it reduces false trading signals that may arise. The sigma used for the computation is the historic standard deviation.

$$Z = \frac{x-\mu}{\sigma} \tag{3}$$

If pairs open and converge during the interval, they will yield positive cash flows. Because pairs can open and close multiple times during the same six-month trading period, they may have multiple cash flows. In addition, pairs will either have a positive or negative cash flow at the end of the trading interval when all positions are closed out. In the case a pair does not open at all, no payoffs will be allocated. Finally, since the gains and losses of the strategy are computed with long–short positions of one dollar, the payoffs can be interpreted as excess returns. These returns are also known as abnormal returns and indicate how well an investment or portfolio has performed relative to the benchmark or the expected return.

An example of a pairs trade is visually presented in Figure 1 below. It can be observed that the spread differs more than 1.5 standard deviations from the mean on July 20th. At this moment, a long position is opened for the Bitcoin since it is undervalued with respect to its mean (the Bitcoin-Ethereum spread is smaller than the rolling mean). The opposite is true for Ethereum hence a short position is opened for this currency. The spread narrows and the z-score crosses 0 on August 13th. As a result, the first position is closed with a total return of 13.6 %. Another position is opened on October 15th with the major difference being that Bitcoin now is overvalued and Ethereum undervalued. As a result a short-long position is opened respectively. The position is closed on December 13th yielding a return of 29.8%. After this event, no more positions are opened for this cryptocurrency pair and thus it yielded a total return of 43.4% in this period.

Figure 1
Z-score of spread: Bitcoin & Ethereum



Note. The graph displays the z-score values according to the daily spread between Bitcoin and Ethereum. These cryptocurrencies were formed into a pair and were traded in the second trading period: July 1, 2021 – December 31, 2021.

4.3 performance metrics

In addition to the excess returns, a variety of other performance metrics shall be used to evaluate the trading strategy. These are the following: Sharpe ratio, downside risk, Sortino ratio, Beta and Alpha.

4.3.1 Sharpe ratio

This ratio is a measure used to access the risk-adjusted return of an investment or portfolio. The Sharpe ratio is calculated by first subtracting the risk-free rate of return from the portfolio return and then dividing this by the portfolio's standard deviation. The risk-free rate of return used in this paper is the US-treasury yield. In general, a higher Sharpe ratio is more favourable. The formula takes the following form:

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p} \tag{4}$$

4.3.2 Downside risk and Sortino ratio

This downside risk focuses on the potential for losses or negative returns on an investment or portfolio. It puts its focus on the risk of unfavourable outcomes, rather than all possible outcomes.

This metric is used to calculate the Sortino ratio, which is a risk-adjusted performance measure similar as the Sharpe ratio. However, the Sortino focuses on downside risk. This ratio is calculated in a similar manner to the previously mentioned ratio, but instead of dividing by the standard deviation of the portfolio, one must divide by the standard deviation of negative return, also known as the downside.

$$Sortino\ ratio = \frac{R_p - R_f}{\sigma_d} \tag{5}$$

4.3.3 Market Alpha and Beta

Beta is a measure used in finance to assess the sensitivity or volatility of an investment's returns relative to the returns of the overall market. Beta is measured as a slope and is calculated through a regression analysis, comparing the historical returns of the investment to the historical returns of the market index. For a Beta coefficient of <1 the investment tends to be less volatile than the market and the opposite is true for a coefficient of >1. If the Beta coefficient equals 0 the investment returns are not correlated with the market returns at all. Since pairs trading is a market-neutral strategy, a Beta of 0 is expected.

$$\beta = \frac{Cov\ (r_i, r_m)}{Var(r_m)} \tag{6}$$

The market Alpha, also known as market risk premium, refers to a portion of an investment’s return that cannot be explained by the market. It represents the excess return generated by an investment above the expected return based on its exposure to market risk. The formula of this metric is derived from the Capital Asset Pricing Model (CAPM) and has the following form.

$$\alpha = R - R_f - \beta(R_m - R_f) \tag{7}$$

CHAPTER 5 Results & Discussion

5.1 Formation results

For the formation of pairs, there had to be calculated first whether enough pairs could be formed. After this was checked the top 10 pairs were selected from each of the three periods. This results in a total of 30 pairs and should be more than sufficient for valid results, since Gatev et al. (2006) drew most of their conclusion based on the results of their top 20 pairs. The pairs for our trading strategy were ranked based on their correlation coefficient between the assets within the pair, which were first tested for cointegration the following way:

Figure 2
Example of the Engle-Granger test for cointegration in Stata 18 MP

reg BMB XMR

predict resid, residuals

dfuller resid

MacKinnon approximate p-value for Z(t)=0.0018

Note. The Figure shows how the Engle-Granger test is performed in Stata 18. First one must run a regression on the two cryptocurrencies. The choice of independence does not matter. Subsequently, the residuals are computed. Finally, an augmented Dickey-Fuller test is performed to check whether or not the residuals are stationary. The result of this test can be observed by looking at the MacKinnon approximate p-value.

As can be seen from Figure 2, the cryptocurrencies BNB and XMR were tested for cointegration following the Engel-Granger method. Out of this test came a p-value of 0.0018, which is smaller than 0.05 thus we can reject the null hypothesis of the presence of a unit root. This means that residuals of BNB (Binance Coin) and XMR (Monero) are stationary and these coins are therefore cointegrated with one another. The correlation coefficient between them is 0.957 and is among the highest correlations between cointegrated pairs, hence they are selected as a pair for the trading strategy. The other 29 pairs were retrieved in a similar manner.

Out of the top 30 pairs, not a single pair consists of a stablecoin. This was to be expected due to the lack of volatility and minimal price spreads these coins display since they are fixed at 1 USD. Therefore, it can be concluded that stablecoins are not suited for pairs trading. As a result, stablecoins will be left out for the remainder of this strategy. While stablecoins might not be well-suited for a pairs trading strategy, they still have other important uses in the crypto market. They facilitate liquidity, provide stability and can act as a medium of exchange (Arner et al. 2020).

5.2 Strategy performance

After a portfolio of the top 30 pairs has been formed, the strategy was backtested in the three different time periods. Table 3 below summarizes the monthly excess returns of the strategy, with its performance metrics and distribution. The first row on the left side of the table first row shows that the average excess return of a pair in this portfolio is 13.9%, with an overall monthly portfolio return of 12%. This finding is economically significant due to its magnitude and the practical application of the strategy. The left side of Table 3 also shows an annualized Sharpe ratio of 3.00. This implies that the strategy has achieved excellent returns compared to its levels of risk. In addition, the annualized Sortino ratio and downside risk are computed. The downside risk is 0.12, which means that the pairs trading strategy used in this study endured limited downside movement or negative returns. The Sortino ratio of 3.11 is quite elevated and this indicates that the strategy experiences high additional return for each unit of downside risk. The portfolio consisting of 30 pairs displays a beta of 1.2 indicating that the portfolio is 20% more volatile than the market. Finally, the table shows an alpha of 0.04, meaning that the strategy outperformed the market by 4%

The right side of Table 3 displays the monthly excess return distribution with a standard deviation of 0.095. The minimum and maximum excess returns are -0.152 and 0.383 respectively. The median excess return is 0 and 37% of the pairs in the portfolio display negative excess returns. The returns are skewed to the right and in addition the kurtosis value is very high. This indicates that there is a higher chance of (positive) extreme values or outliers compared to a bell-shaped curve.

Table 3
Excess returns of pairs trading portfolio

Performance metrics	x	Distribution metrics	x
Average excess return	0.139	Standard deviation	0.095
Monthly excess return	0.115	Median	0
Sharpe ratio	3.00	Minimum	-0.152
Downside risk	0.12	Maximum	0.383
Sortino ratio	3.11	Skewness	1.839
Beta	1.20	Kurtosis	8.452
Alpha	0.04	Observations with negative returns (%)	37%

Note. The table displays performance and distribution metrics of a portfolio consisting of the top 30 cryptocurrency pairs between January 2020 and December 2022. Pairs are formed over a 6-month period according to the highest correlation coefficient between them and they are traded the subsequent 6 months. The trades follow a pre-specified rule where a long-short position is opened when the price diverges by more than 1.5 historical standard deviations and the position is closed when the prices cross. The left side of the table provides metrics to evaluate the performance of the strategy where the Downside risk and Sharpe/Sortino ratio are annualized. The right side provides information about the distribution of the monthly returns.

Table 4 displays the output of performing a classical mean comparison test with unknown variance, also known as the t-test. It is tested whether the monthly returns are significantly larger than zero (one-tailed). The pairs trading strategy reports higher excess returns (M= 0.1157, SD= 0.0945) than what would be expected by the norm, $t(29) = 6.7$, $p < 0.05$. The pairs trading strategy reports a t-statistic which at a degrees of freedom of 29 easily surpasses the critical value of 1.699 (one-tailed) at a 95% confidence level. This implies that the null hypothesis of no evidence for positive excess returns can be rejected. Therefore, there is strong statistical evidence to conclude that the strategy yields positive excess returns in the crypto market. This can also be observed by the p-value which is smaller than 0.05.

Table 4
One-sample t-test of pairs trading strategy

Variable	Mean	Std. dev.	t	df	Sig.
Returns	**0.1157**	**0.0945**	**6.7**	**29**	**0.0000**

Note. The table shows the output of performing a t-test on the monthly excess returns of the pairs trading strategy. The degrees of freedom is 29, due to the portfolio consisting of 30 pairs. The significance is tested on a 95% confidence level.

Table 5 provides information about the trading statistics. In the first row can be observed that the average round trips per pair in our portfolio (from open to closed) is 1. The minimum number of round trips is 0 for pairs that did not open and the maximum number of round trips a pair displayed in a single period is 4. Out of the 30 pairs, a vast majority of 24 pairs have been traded (which means they opened a short/long position). Finally, the average time pairs were opened is 90 days, which indicates that pairs trading is a medium-term strategy.

Table 5
Trading statistics of pairs trading strategy

Crypto Pairs portfolio	x
Average number of round trips per pairs	1
Minimum number of round trips	0
Maximum number of round trips	4
Number of pairs traded	24
Average time pairs are opened (days)	90

Note. Trading statistics of a portfolio of top 30 cryptocurrency pairs between January 2020 and December 2022. Pairs are formed over a 6-month period according to the highest correlation coefficient between them and they are traded the subsequent 6 months. The trades follow a pre-specified rule where a long-short position is opened when the price diverges by more than 1.5 historical standard deviations and the position is closed when the prices cross.

Discussion

From the previous section can be observed that the average excess return is 13.9%, The average excess return of a pair per period is -6.67%, 38.10% and 10,24 % respectively. Periods 1 and 3 have excess returns relatively close to the market expectations around 0%. Contrarily, the second period stands out with outlying results. A possible explanation for this phenomenon is the huge volatility the crypto market experienced in 2021. For example, the bitcoin fluctuated in this period from around $30000 to $64000 with a relatively high volatility of 19% in the second trading interval. This finding is similar as Rad et al (2016) who found evidence for an increased effectiveness of pairs trading in volatile markets. The huge success of the strategy in this period can also partially be explained by the fact that pairs trading performs better during financial crisis, which was found to be the case by Gatev et al (2006) and Do & Faff (2010). In the year 2021, the world faced economic uncertainty since society was coping with the covid-19 pandemic. However, the returns for the first period in 2020 are found to be negative in our strategy whereas according to this theory one would presume the returns to be skyrocketing during the start of the pandemic.

Regarding the strategy's Sharpe ratio, a ratio of 3.00 is quite elevated and implies that the strategy has generated high returns compared to the amount of risk taken. This shows that there is not much room to improve the risk-adjusted performance of the strategy. However, The Sharpe ratio could still be improved by reviewing the entry/exit positions or the pairs selection criteria. This research used the correlation method, which was less popular than the cointegration or distance method used in benchmark literature. Substituting these methods could possibly increase the Sharpe ratio. Lastly, it was shown by Goetzmann et al. (2002) that Sharpe ratios can be misleading when the distribution of returns contains a negative skewness. This bias is unlikely to be true in this study since the skewness coefficient has a positive value of 1.8.

In addition, the strategy was expected to display a Beta of 0 due to pairs trading being market neutral. However, this is not the case with the pairs trading portfolio displaying a Beta of 1.2. This indicates that the strategy is 20% more volatile than the market, where the Crypto10 Index is taken as a benchmark. The value of Beta suggests that the assets chosen for this strategy may have a stronger correlation with the overall market than anticipated. In addition, the portfolio may be more exposed to systematic risk. The Alpha of 4% suggests that the portfolio has outperformed the benchmark Crypto10 index. It indicates that the portfolio's returns have exceeded what would be predicted by its exposure to systematic market risk. The ability of the portfolio to consistently generate positive alpha is considered a sign of skill or expertise, indicating that the strategy has added value beyond what can be explained by market movements.

Another case to be discussed is the presence of transaction costs. The returns for this pairs trading strategy have been economically significant with a monthly excess return of 12% and an average excess return of 13.9%. However, in practice transaction costs must be accounted for. The leading cryptocurrency exchange Binance charges between a 0% and 0.60 % spot trading fee. If a conservative estimate of 0.60% is taken, the strategy still yields a monthly return of 10.58% and an average excess return of 12.7%.

In addition to the strategy yielding economically significant returns, there is enough statistical evidence for rejecting the null hypothesis of no evidence for positive excess returns. The displayed returns are not due to chance and therefore the conclusion can be drawn that pairs trading yields positive excess returns in cryptocurrency markets. This is similar to Kirstoufek et Fil (2020) proving that pairs trading is a profitable strategy. In the paper they used a smaller sample size, but the main different lies in the fact that the cointegration- and distance method were used instead of the correlation method. It is interesting to see that a different pair selection method still yields somewhat similar results. Saji (2021) is another paper that has comparable findings proving that pairs trading with cryptocurrencies yield positive returns and that it consistently beats the general buy/hold strategy. In that paper the author has used another formation method and a sample size of 4 cryptocurrencies. It can therefore be concluded that pairs trading is a very versatile strategy which can be adjusted in a variety of ways.

At the start was expected that the pairs trading strategy in this study underperforms previous benchmark literature. This concern was present due to the fact that Gatev et al (2006) and Do & Faff (2010) noticed a decreasing trend in the probability of a pairs trading strategy. However, the results of this study don't show any sign of concern. Although, it could be very much possible that their findings are true with respect to the equity market, but that the crypto market refuses to give in. The crypto market is a relatively new and unpredictable market and it can therefore be quite tricky to make any predictions for the future.

CHAPTER 6 Conclusion

In this thesis the profitability of pairs trading in the crypto market was examined. Previous research has shown that performing a pairs trading strategy with the use of cryptocurrencies yields positive excess returns, but that it underperforms benchmark literature which uses the stock market. Existing literature uses the cointegration or distance method to form pairs. However, this strategy has not yet been tested by using the correlation method for formation. In addition, previous studies have displayed a decreasing trend in the profitability of the strategy over the years. Therefore, the question that was studied in this dissertation was: “Does pairs trading in cryptocurrency markets still display positive excess returns?” To answer this research question, the closing price data of 50 cryptocurrencies have been observed over a 3-year period. With these closing prices, 30 pairs were formed which was followed up by backtesting the trading strategy following pre-specified rules. After analyzing the strategy, there was evidence of pairs trading displaying positive excess returns. In addition, the strategy indeed performed better during financial crisis and the results were robust to transaction fees, agreeing with benchmark literature. Finally, there was no sign of a decreasing trend in the profitability of the trading strategy. With the emergence of artificial intelligence, it would be interesting to study the use of machine learning in the field of pairs trading in crypto markets.

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APPENDIX A - Arbitrary choice of (in)dependent variable Engle-Granger test

This appendix contains visual representation to underpin the arbitrary choice of the independent and dependent variable for the Engle-granger test. Figures 3 and 4 display the same Engle-Granger test with the only difference being the dependent and independent variable. Figure 3 choses QNT as dependent variable whereas Figure 4 choses VET as dependent variable. From the figures can be observed that alternating the choice of dependent variable only changes the coefficient by 0.001. This impact of 0.1% is insignificant for determining if a pair is cointegrated or not. Repeating the same process in Figure 5 and Figure 6 while adjusting the dependent variable to HBAR and CRO respectively yields a difference of 0.2%. Repeating this process multiple times leaves a clear trend of low impact on coefficient by altering. To be completely sure, pairs in the sample with coefficients close to the 5% mark were checked and the choice of (in)dependent variables did not impact the results. These findings in addition to the explanation given in section 4.1.1 lead to the conclusion that the choice for independent and dependent variables for performing an Engle-Granger test does not matter for the formation results of the pairs trading strategy used in this paper.

Figure 3:
Engle-Granger test with QNT as dependent asset and VET as independent asset

reg QNT VET
predict resid, residuals
dfuller resid

MacKinnon approximate p-value for Z(t)=0.0190
Note. The Figure shows how the Engle-Granger test is performed in Stata 18. First one must run a regression on the two cryptocurrencies. Subsequently, the residuals are computed. Finally, an augmented Dickey-Fuller test is performed to check wether or not the residuals are stationary. The result of this test can be observed by looking at the MacKinnon approximate p-value.

Figure 4:
Engle-Granger test with VET as dependent asset and QNT as independent asset

reg VET QNT
predict resid, residuals
dfuller resid

MacKinnon approximate p-value for Z(t) = 0.0180
Note. The Figure shows how the Engle-Granger test is performed in Stata 18. First one must run a regression on the two cryptocurrencies. Subsequently, the residuals are computed. Finally, an augmented Dickey-Fuller test is performed to check whether the residuals are stationary. The result of this test can be observed by looking at the MacKinnon approximate p-value.

Figure 5
Engle-granger test with HBAR as dependent asset and CRO as independent asset

```
reg HBAR CRO
predict resid, residuals
dfuller resid
```

MacKinnon approximate p-value for Z(t) =0.0578

Note. The Figure shows how the Engle-Granger test is performed in Stata 18. First one must run a regression on the two cryptocurrencies. Subsequently, the residuals are computed. Finally, an augmented Dickey-Fuller test is performed to check whether the residuals are stationary. The result of this test can be observed by looking at the MacKinnon approximate p-value.

Figure 6
Engle-Granger test with CRO as dependent asset and HBAR as independent asset

```
reg CRO HBAR
predict resid, residuals
dfuller resid
```

MacKinnon approximate p-value for Z(t) =0.0558

Note. The Figure shows how the Engle-Granger test is performed in Stata 18. First one must run a regression on the two cryptocurrencies. Subsequently, the residuals are computed. Finally, an augmented Dickey-Fuller test is performed to check whether the residuals are stationary. The result of this test can be observed by looking at the MacKinnon approximate p-value.