FUNDAÇÃO GETULIO VARGAS
ESCOLA DE ADMINISTRAÇÃO DE EMPRESAS DE SÃO PAULO

BRENDAN PADRAIC ANSON PRITCHARD

DIGITAL ASSET ARBITRAGE

SÃO PAULO
2018

Pritchard, Brendan Padraic Anson-.
Digital asset arbitrage / Brendan Padraic Anson Pritchard. - 2018.
60 f.

Orientador: Samy Dana.
Dissertação (MPGC) - Escola de Administração de Empresas de São Paulo.

1. Operações com pares (Finanças). 2. Transferência eletrônica de fundos. 3. Bitcoin. 4. Câmbio. 5. Ações (Finanças). I. Dana. Samy. II. Dissertação (MPGC) - Escola de Administração de Empresas de São Paulo. III. Título.

CDU 336.74

Ficha catalográfica elaborada por: Isabele Oliveira dos Santos Garcia CRB SP-010191/O
Biblioteca Karl A. Boedecker da Fundação Getulio Vargas - SP

BRENDAN PADRAIC ANSON PRITCHARD

DIGITAL ASSET ARBITRAGE

Applied Thesis presented to Escola de Administração de São Paulo da Fundação Getúlio Vargas, as required to obtain the title of Professional Master in Management for Competitiveness.

Advisor: Samy Dana

SÃO PAULO
2018

BRENDAN PADRAIC ANSON PRITCHARD

DIGITAL ASSET ARBITRAGE

Applied Thesis presented to Escola de Administração de São Paulo da Fundação Getúlio Vargas, as required to obtain the title of Professional Master in Management for Competitiveness.
Advisor: Samy Dana

Date of Defense 29/05/2018

Examination Board:

____
Prof. Dr. Samy Dana
(Advisor)
FGV – EAESP

____
Prof. Dr. Hsia Hua Sheng
FGV – EAESP

____
Prof. Dr. Bruno Giovanetti
FGV – EESP

Dedicated to my mother Christine,
my family, and all those who have
motivated me along the way.

ABSTRACT

The study examines the risk and reward potential of arbitrage in the digital asset market. Specifically, it looks at exchange to exchange and statistical arbitrage, or pairs trading, for the cryptocurrencies, Bitcoin (BTC) and Litecoin (LTC). In this instance they are traded on the LTC/BTC pair. The LTC/BTC is examined with pairs trading by performing statistical tests and implementing automated trading strategy to determine potential profit levels. Subsequently, additional trading strategies are examined based on the concepts of the statistical results in this study and other technical analysis indicators. The study outlines the profit potential of exchange to exchange arbitrage but also shows how this type of arbitrage is in fact quite risky and not as simple as the large spreads would suggest. Pairs trading strategies are instead put forward as a method of profiting on the price movement disparities in the digital asset market without running the same risks as exchange to exchange arbitrage. The strategies proposed are based on statistical tests as well as technical analysis indicators that both aim at predicting price trend and direction and try to profit off abnormal price movements and subsequent normalization. It turns out that a range of profit levels can be achieved. All though the strategies proposed are too rudimentary to consider for live trading, they do prove the basic proof of concept that there are ways to profit from pairs trading in the digital asset market. Trading strategies can be formed that provide considerable returns while reducing risk that would otherwise be encountered with long term investment positions and/or exchange to exchange arbitrage in the digital asset market.

Keywords: Digital Assets, Cryptocurrency, Bitcoin, Litecoin, Arbitrage, Exchange to Exchange, Pairs Trading.

RESUMO

O seguinte estudo examina o potencial de risco e recompensa de arbitragem no mercado de ativos digitais. Especificamente, analisa a arbitragem entre bolsas de cryptomoeda e arbitragem estatística, ou *pairs trading*, para as cryptomoedas, Bitcoin (BTC) e Litecoin (LTC). Neste caso, elas são negociadas no par LTC/BTC. O LTC/BTC é examinado em pares e negociadas por meio da realização de testes estatísticos e implementando a estratégia de negociação automatizada para determinar os níveis potenciais de lucro. Subsequentemente, estratégias adicionais de negociação são examinadas com base nos conceitos dos resultados estatísticos deste estudo e outros indicadores de análise técnica. O estudo delineia o potencial de lucro de arbitragem entre bolsas, mas também mostra como esse tipo de arbitragem é, na verdade, bastante arriscado e não tão simples quanto as grandes margens sugeririam. Estratégias de negociação em pares são apresentadas como um método de lucrar com as disparidades de movimento de preços no mercado de ativos digitais, sem correr os mesmos riscos que a troca por arbitragem de câmbio. As estratégias propostas baseiam-se em testes estatísticos, assim como em indicadores de análise técnica que visam prever a direção e a tendência do preço e tentar lucrar com movimentos ou tempos anormais de preços e normalização subsequente. Ficou comprovado que diferentes de níveis de lucro podem ser alcançados. Embora as estratégias propostas sejam rudimentares demais para serem consideradas para negociação com dinheiro vivo, elas provam o conceito básico de que existem maneiras de lucrar com a negociação de pares no mercado de ativos digitais. Estratégias de negociação podem ser formadas, proporcionando retornos consideráveis e, ao mesmo tempo, reduzindo o risco de que outra forma seja encontrada em posições de investimento de longo prazo e / ou em troca de arbitragem de câmbio no mercado de ativos digitais.

Palavras-chave: Ativos Digitais, Cryptomoeda, Bitcoin, Litecoin, Arbitragem, Bolsa, Arbitragem Estatística.

INDEX OF FIGURES AND CODE

INDEX OF APPENDIXES

SUMMARY

1. INTRODUCTION

Arbitrage opportunities appear in numerous occasions in the digital asset markets. Profitable spreads are seen across different exchanges, regions, and asset pairs. There are market operators constantly trading on these market disparities, many in an automated fashion. The efforts are not sufficient to maintain parity and opportunities are still prevalent in market. The market imperfections are magnified between regions with low and high capital controls presenting larger, more attractive spreads. Examining price levels in low capital control markets such as EU or USA, compared to markets such Brazil or most notably, Korea.

The exchange to exchange (e2e) arbitrage opportunities are more difficult than they appear to earn a risk-free profit. There are many challenges to a trader that wants to take advantage of price disparities and is not at the same time a market maker or keen on holding long term positions. The risks and barriers to successful profiting on digital asset arbitrage can be considered high. The trading strategies that employ the concepts of statistical arbitrage can provide advantages to e2e arbitrage by reducing risk and side stepping the barriers that the latter presents.

Pairs trading, a form of statistical arbitrage, is a strategy that can provide profit potential in the market. The crypto currencies Litecoin and Bitcoin are examined with pairs trading techniques using statistical tests and automated trading strategy to determine profit levels. Subsequently, additional trading strategies are examined based on the concepts of statistical results in this study and other technical analysis indicators.

2. LITERATURE REVIEW

2.1. BITCOIN

2.1.1. MARKET CHARACTERISTICS AND BARRIERS

Bitcoin (BTC) is the oldest digital asset on the global markets. It has existed since 2009 and is the most widely traded cryptocurrency in terms of volume, number of markets, number of trading pairs, both with other digital and fiat currencies, and number of regions according coinmarketcap.com. The number one position makes it a desirable currency to exploit arbitrage opportunities. From 2017 to 2018, the spread ranges from -6% to +38% and has a median of 5% and average of 7% between the Brazilian Exchange Mercado Bitcoin and the European Exchange Bitstamp. Looking at the potential returns for the purest arbitrage opportunities makes the digital asset market an attractive market for low risk and low effort trading. However, examining only at the potential returns and operation in a traditional sense without considering the barriers and risks of trading in these new markets is a recipe for disasters as the pitfalls in this market differ greatly from traditional capital and commodity markets.

The most important barrier to consider when examining potential arbitrage opportunities in the digital assets market is volume. Volume is king and no matter how large a spread is, it will also be the major determining factor in the extent of returns. The average daily volume on the BTC/USD market was 23,000 BTC, just for Bitstamp and on the Brazilian exchange Mercado Bitcoin, it was only 360 BTC. The clear takeaway is that volume on the Brazilian exchange is substantially lower than the European exchange, averaging about 1.6% volume traded. Therefore, the principal restricting barrier to profits in this scenario is volume on the Brazilian exchange. Since the asset will be acquired on the European exchange and sold on the Brazilian exchange, the volume on the Brazilian exchange will need to be high enough to support the selling of BTC without dramatically

reducing the price, and subsequently the spread and profit margin. Since the volume is so large on Bitstamp compared to Mercado Bitcoin, it's safe to say that the movement on Bitstamp will always be superior.

Another strategy is selling on multiple Brazilian exchanges. Even though the combined volume of the main exchanges will still be less than 10% of Bitstamp volume, it will at least provide more market depth for the arbitrage opportunities. The result would be more slightly more complex opportunity on two exchanges with somewhat different setups and fee structures. More importantly, operating on multiple exchanges not only increase the effort and complexity of the arbitrage exploitation strategy, it also bares increased risks to an already high-risk operation.

2.1.2. RISKS

Volatility is one of the hallmark risks of cryptocurrency markets. Bitcoin is no exception to this volatility and wild price swings in either direction are not uncommon. These price swings provide profitable opportunities for traders however, in an arbitrage operation, a dramatic price move can erode profits and make the operation inviable. The volatility index for bitcoin is rated varied between 2% and 8% compared to gold and fiat which have volatility index levels around 1.2% and .05% – 1 % respectively. In the case of non market makers, transaction speed is a risk inherent for any cryptocurrency arbitrage operation between exchanges. In short, sending coins from one exchange to another takes time. The time it takes varies depending on the coin and network traffic. Bitcoin, being the first cryptocurrency and most disseminated digital asset, has one of the slowest transaction speeds and historical tendency to accumulate a backlog of transactions. The bitcoin network can only confirm transactions at a speed of three to seven transactions per second. Since the coins need to move between exchanges, the speed at which a transaction takes becomes a bottle neck on the operation. The amount of time is not guaranteed and therefore the risk can only be estimated. The exposure leaves the

operation vulnerable to price movement while coins are being transferred to the destination exchange in order to sell. The risk is not small and even worse, it's hard to change or calculate with precision.

Digital asset exchanges are a nascent service provider industry. Due to recent popularity, many exchanges are at or over capacity. The trading platforms they run are subject to technical problems. Platforms can experience latency or complete downtime during high volume trading periods. In addition, they can completely go offline and take days to restore services. Compromised service for an exchange can severely jeopardize an arbitrage operation and there is only so much a trader can do to hedge this risk. The market keeps moving and when service is restored the operation could be loss making. The only way to reduce the exposure is use more than one historically reliable exchange. A multiple exchange strategy reduces the risk of the entire trading capital being taken off the table but increases the chance that some of your trading capital will be taken of the table. Additionally, there are different prices in between different which further complicates the operation.

Wallet and exchange security are essential to a complete arbitrage opportunity. It goes without saying that profits cannot be obtained if they are lost or stolen. Wallet is where coins are stored at an individual level and can be comprised if not protected with passwords just the same as any trader would protect their personal information for any other account. The responsibility to reduce the risk in this regard rests almost entirely on the shoulders of the trader. However, exchanges can also go down, and they can leave account holders with serious loss potential turning any opportunity into a complete disaster. There are dozens of horrors stories of exchanges getting hacked but the most prominent being Mt. Gox, which resulted in insolvency of the exchange and litigation that started in 2014 and extends until present day. The challenges presented by bitcoin demand that a less risky approach is taken.

2.2. LITECOIN

2.2.1. MARKET CHARACTERISTICS

Litecoin is another cryptocurrency based on the Bitcoin protocol. It's similar in many fashions, but more importantly it is a top 10 market capitalization coin. It's traded on many markets across the world, and many of the same exchanges as BTC. It has liquidity and experienced significant increase in value in 2017 along with BTC and many other digital assets. LTC presents an interesting arbitrage opportunity. The asset is traded in Brazil and shows similar spreads for arbitrage potential when compared to exchanges abroad. The spread ranges from -9.5% to +45% and has a median of 5% and average of 6.5% between the Brazilian Exchange Mercado Bitcoin and the European Exchange Bitstamp. Similarly, the spreads are considerable and the plot skews to allow for more upside vs potential downside assuming the direction of the arbitrage strategy.

2.2.2. ADVANTAGES AND DISADVANTAGES

LTC has pros and cons compared to BTC but the pros tend to favor the coin for the opportunity as to the cons which tend to only limit the absolute level of profitability of the opportunity. The most attractive attribute of LTC when it comes to arbitrage trading is the network's transaction speed. The Litecoin network can process between 26 and 56 transactions per second. The Litecoin network is therefore many times faster than the bitcoin network. The Litecoin network is also used less compared to bitcoin so there is less of a chance of a back log meaning the transaction time is more dependable in the practical sense. From the arbitrage perspective, transaction speed and minimal network congestion allow for positions to be moved between exchanges faster and therefore reducing any potential downside in price changes while operations are undergoing execution. Taking the advantage of faster transaction speed into consideration makes LTC a better arbitrage. However, the opportunity remains limiting.

LTC, although a top 10 market capitalization coin, has low volume compared to BTC. Of course, inter-day fluctuations change but from 2017 to 2018 the volume has more or less been about 10% of BTCs. The result is volume which is less capable of supporting a price at any given level compared to BTC should a trader take advantage of the opportunity. Of course, the opportunity still exists, but the size of the potential can only be supported by the size of the volume. All factors considered, an arbitrage strategy attempted in the LTC markets can still not satisfy the risk/reward appetite of a trader, especially when compared to the daily swings of the stand-alone assets. A more elaborate trading strategy such as pairs trading, can potentially satisfy the desire to profit off the volatility and inter-exchange spread while at the same time reducing risk factors and trading barriers.

2.3. PAIRS TRADING - LTC/BTC

Pairs trading is a strategy that can be used to take advantage of arbitrage opportunities in the digital asset markets. The strategy, sometimes referred to as statistical arbitrage, exploits abnormal pricing relations between correlated assets. The strategy is often implemented in similar asset classes, exchange traded funds, and other securities that have a degree of correlation. When the normal correlation falls out of balance, a market neutral position is taken in order to profit from the rebalancing of the ratio. In short, the strategy profits off the deviation from a normal correlation by betting that the normal balance will be soon be restored.

Pairs trading was first implement in the 1980s by a team at Morgan Stanley of quantitative analysts. They developed the idea in order to work on automated trading strategies to profit from the mispriced assets. The strategy has proved profitable over the years as more traders have taken it up and doubled down on the quantitative approach in order to exploit profits. Pairs trading is sometimes referred to as statistical arbitrage

but basically any pairs trading strategy can be classified in two groups, mean reverting or trend following. Mean reverting, as the name explains, bets that correlated assets will revert to the mean should the correlation deviate more than normal, or in other words, be mismatched. Trend following strategies trade in the direction of a price rather than against. (Vidyamurthy, 2004).

In order to simulate pairs-trading in the digital asset markets, LTC and BTC are used as they are both large-cap crypto currencies. The two currencies can be traded on the ratio pair, LTC / BTC or versus other crypto/fiat currencies. In the traditional asset trading world, pairs of stocks are selected using automated programs which are able to identify pairs that tend to move tightly together in terms of price ratio. Options are limited in the digital asset markets and in order to have enough data, market availability, and robust asset class, large cap / large volume, LTC and BTC are selected. The following figures show the price movement of both currencies from 2017 to 2018.

Figure 1. Bitcoin and Litecoin prices in BRL from Jan. 2017- Mar. 2018 Data for Bitcoin and Litecoin MercadoBitcoin Investing.com

Figure 2. Bitcoin and Litecoin in USD prices from Jan. 2017- Mar. 2018 Data for Bitcoin and Litecoin USD Bitstamp Investing.com

Examining the ratio in both BRL and USD, it's apparent that the two ratios move in sync even though the markets are in different geographical locations. Therefore, how the two ratios move compared to one another shouldn't be much different and it appears these two coins do indeed have a positive correlation. The following figure compares the ratio for both BRL and USD.

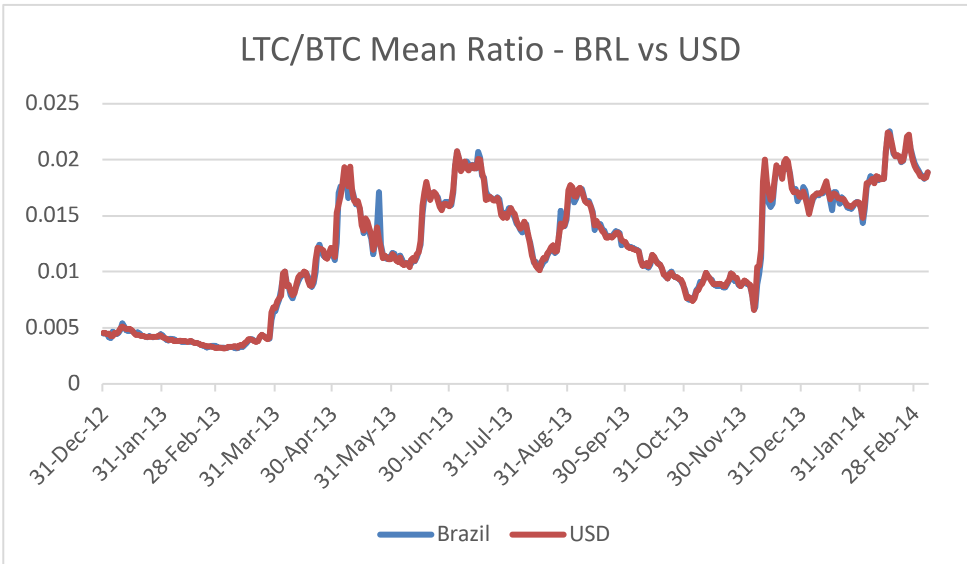

Figure 3. Litecoin/Bitcoin BRL vs USD ratio from Jan. 2017- Mar. 2018. Data for Litecoin/Bitcoin BRL from MercadoBitcoin via Investing.com. Data for Litecoin/Bitcoin USD Dollar from Bitstamp via Investing.com

Figure 4. Litecoin/Bitcoin ratio from Jan. 2017- May. 2018. Data for Litecoin/Bitcoin Ratio from Poloniex via cryptowat.ch/markets/poloniex/ltc/btc/3d

It’s clear that there is a trend in this ratio however, there is significant movement over the course 10-11 months where the ratio trades in a specific trading range. The range falls more or less between the 61.80% and 23.60% Fibonacci retracement levels when they are overlaid on the 3-day timeframe. From April 2017 to current time, the ratio has bounced several times between these levels as the entire digital asset market experienced an increase in value, or a bull run. At the times the ratio has slipped out of the bottom or peaked above the top of the trading range but for the most part of the macro series, it traded within this range. Taking this into consideration leads to the logical question of whether a pairs trading strategy can be formulated with either mean reversion or trend techniques to deliver lower risk profit.

3. METHODOLOGY

3.1. STATISTICAL ANALYSIS

The methodology for studying the arbitrage opportunity in Brazil is mainly a combination of automated trading strategies based on technical analysis and statistical tests performed in the program R, a programming language and free software environment for statistical computing. The trading strategies, for their part, are implemented and back tested in Zorro, and open source automated trading software. Bitcoin and Litecoin are examined with pairs trading with statistical tests and automated trading strategy to determine profit levels. Subsequently, additional trading strategies are examined based on the concepts of statistical results in this study and trend and mean reversion techniques. The study starts by following parts of the models of Kris Longmore from Robot Wealth and Ernest Chan’s work on algorithmic trading.

3.2. THE AUGMENTED DICKEY FULLER (ADF)

Statistical analysis of the LTC/BTC pair is starting point to formulating trading strategies. There are analyses that test series in different ways to determine if it is mean reverting, trending, or a random walk. The LTC/BTC individual time series is studied to for potential mean reversion in order to build a profitable trading strategy. The Augmented Dickey Fuller (ADF) test is one example of a test that determines if the time series has a unit root, and mean-reverting. If the time series is not a random walk then present values will shed light on what the next value in the series may be. Should the series be mean reverting then it's expected that a value above the mean will be followed by a value below the mean and so on and so forth.

Examining a linear model of price changes:

$$\Delta y(t) = \lambda y(t-1) + \beta t + \mu + \alpha 1 \Delta y(t-1) + \ldots + \alpha k \Delta y(t-k) + \varepsilon t$$

$$\text{where } \Delta y(t) \equiv y(t) - y(t-1),\ \ \Delta y(t-1) \equiv y(t-1) - y(t-2), \text{ etc.}$$

According to the formula, $\lambda \neq 0$ then $\Delta y(t)$ depends on the current level $y(t-1)$ and therefore is not a random walk. In the ADF test, the null hypothesis, $\lambda = 0$ is tested to see if it can be rejected and various levels of confidence. The ADF test is applied on Longmore's R code several R packages that form the basis of the tests. The drift term is zero since the constant drift in price is usually a smaller magnitude than the daily fluctuations in price (Chan, 2013). However, the intercept is set to be non-zero. The combination of these two settings is accomplished by using the drift argument contained in R program. A lag of 0 is used to start, but that improved results are normally obtained with a greater lag of 1, which can indicate potential serial correlation of price movement as recommended by (Chan 2013).

Looking back at the bull run experienced by BTC, LTC, and other digital assets, it could be expected that a degree of mean reversion exists in this period given that the

currencies are both similar in nature besides both being large capitalization coins. BTC tends to have an effect on other coins and on the general market in a similar way that the tide brings boast up and down. As it rises, it brings other digital assets up with it and as it falls, other assets tend to go in the same direction. The reason for this behavior is because of its number one market cap position with over 40% over the market and the numerous pairs of the different coins that trade directly against BTC. Due to these similar market factors for LTC/BTC, it's possible to determine mean reversion.

The results of the ADF test in R are:

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################
Test regression drift
Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)
Residuals:
       Min         1Q     Median         3Q        Max
-0.0023442 -0.0003754 -0.0001267  0.0002599  0.0047825

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.011e-04  9.593e-05   2.096   0.0366 *
z.lag.1     -1.414e-02  7.036e-03  -2.009   0.0450 *
z.diff.lag   3.286e-02  4.549e-02   0.722   0.4705
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0008255 on 481 degrees of freedom
Multiple R-squared:  0.009043,Adjusted R-squared:  0.004923
F-statistic: 2.195 on 2 and 481 DF,  p-value: 0.1125

Value of test-statistic is: -2.0095 2.2185

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.44 -2.87 -2.57
Phi1  6.47  4.61  3.79
```

Note. Augmented Dickey-Fuller Test Unit Root Test produced in program R.

The λ term in the linear model above is the estimate of z.lag.1 divided by the corresponding standard error. The critical values correspond to tau2. In this result, the test statistic is -2.0095 which is greater than the 10% critical value, so the null hypothesis that $\lambda=0$ cannot be rejected even at the 90% certainty. Therefore, the conclusion is reached that the time series is indeed not mean reverting.

3.3. THE HURST EXPONENT

Statistical analysis of the LTC/BTC pair is starting point to formulating trading strategies. There are analyses that test series in different ways to determine if it is mean reverting, trending, or a random walk. As Ramos points out in her work, "One of the well-known stylised facts of finance is that financial time series exhibit mean reversion patterns in different degrees and at different times." (Ramos 2017 pg. 4) The LTC/BTC time series is studied to for potential mean reversion on order to build a profitable trading strategy. There are other ways of examining the mean reversion of the series. The Hurst exponent is a tool that measures the long-term memory of a time series, in this case LTC/BTC. The test relates to the autocorrelations of the time series and the rate at which these decline as the lag between pairs of values expand. The Hurst Exponent does this by calculating the rate of diffusion from its original state. As Ramos explains "As we pointed out in previous sections, in pair trading, researchers look for correlated (or cointegrated) stocks, since then the pair will have reversion to the mean properties, so it seems natural to look for pairs with low Hurst exponent in order to apply reversion to the mean strategies." (Ramos 2017 pg 6) Should the series be mean reverting, it will diffuse at a slower rate than a geometric random walk. The rate of diffusion, presented as the variance of the series can be measured as such:

$$\mathrm{Var}(\tau) = \langle |z(t + \tau) - z(t)|^2 \rangle$$

where

- **z = log(price)**
- **τ is an arbitrary time lag**

- **⟨…⟩ is an average over all t's**

For a series that is a geometric random walk the result is:

$$\langle|z(t+\tau) - z(t)|^2\rangle \sim \tau$$

Should the series be either trending or mean reverting, the relationship the result will be

$$\langle|z(t+\tau) - z(t)|^2\rangle \sim \tau^{2H}$$

The variable H is the Hurst exponent and it serves to indicate the degree to which a series, in this case price movement, trends. When $H > 0.5$ the series is trending. When $H < 0.5$, the series is mean-reverting. Finally, if $H = 0.5$, the series is a geometric random (Chan, 2013). In R the Hurst calculation renders a list of the adjusted and corrected values for H. The following results are the Hurst calculations for the LTC/BTC pair.

1 Simple R/S Hurst estimation: 0.8342654
2 Corrected R over S Hurst exponent: 1.005085
3 Empirical Hurst exponent: 1.030827
4 Corrected empirical Hurst exponent: 1.005198
5 Theoretical Hurst exponent: 0.5465102

Note. Hurst Test Result for LTC/BTC produced in program R.

The results provided by the Hurst calculation conclude that the series not mean reverting, it is in fact trending.

3.4. HALF-LIFE MEAN REVERSION, ORNSTEIN-UHLENBECK STOCHASTIC PROCESS

Statistical proofs with high levels of confidence, are useful in formulating trading strategies but reaching these demanding levels does not guarantee strategy to be profitable. In a similar sense, the levels of confident required by statistical tests do not negate a profitable strategy should their levels not be met. It is useful in this case to use statistical tests to guide strategy formulation, but also deviate from their strict requirements when its deemed necessary (Longmore 2015). After all, the data from the pair must be traded as is provided. Calculating the half-life of a mean reversion can be

used to build a mean reversion trading strategy. The previously calculated lambda coefficient as can be interpreted alternatively as to the time necessary for the series to mean revert. (Chan, 2013). For the alternate understanding to be seen, the model used above can be converted into a differential form. The form is equal to the statistical test, Ornstein-Uhlenbeck Stochastic Process. The formula for the statistical test is as follows:

$$dy(t) = (\lambda y(t-1) + \mu)dt + d\varepsilon$$

where ε is Guassian noise. These differential forms lead to an analytical solution for the expected value of $y(t)$:

$$E(\ y(t)) = y_0 \exp(\lambda t) - \mu/\lambda(1 - \exp(\lambda t))$$

In the case of a mean reverting process where the value of λ is negative, it suggests that the expected value of the price decays exponentially at a half-life of $-log(2)/\lambda$. Should the value of λ be positive, the price series is then considered trending. In this event, a mean-reverting strategy will not work. Finally, should the value of λ be close to zero, the half-life will be very long. A long half-life indicates an inviable trading strategy as positions would need to be held for long periods. If λ is considerably negative, it increases the chances that a profitable and practical mean reversion strategy exist due to the fact that the price series tends to revert to the mean at a quicker pace. In his discussion of this notion, Chan also states that λ should be used in calculating the lookback periods of moving averages and standard deviations in order to use in a mean reverting strategy. A small multiple of the λ value is optimal in such occurrences. (Chan 2013)

The subsequent R code determines the half-life of the mean reversion for the LTC/BTC trading history. The variable λ is regress $y(t) - y(t-1)$ against $y(t-1$.

```
##########
# Calculate half-life of mean reversion

y <- ltcbtc
y.lag <- lag(y, -1)
delta.y <- diff(y)

df <- cbind(y, y.lag, delta.y)
df <- df[-1 ,]

regress.results <- lm(delta.y ~ y.lag, data = df)

lambda <- summary(regress.results)$coefficients[2]
half.life <- -log(2)/lambda
```

Note. Half-life code for program R.

In the instance of LTC/BTC, the half-life is calculated to be 50.4 days. The calculation of the half-life can be utilized in trading strategy in order to make this information profit to the trader's advantage.

3.5. JOHANSEN TEST FOR COINTEGRATION

Pairs trading is commonly implemented by beginning with assets pairs that cointegrate to exploit mean reversion. The luxury of selecting an optimal cointegrating pair of assets isn't possible because the only two digital assets available are BTC and LTC. Up until this point, mean reversion of individual financial time series has been examined by applying such techniques as the Augmented Dickey-Fuller test, the Hurst exponent and the Ornstein-Uhlenbeck equation for a mean reverting stochastic process. These tests guided the pairs trading strategy from a market neutral approach, even though the series is not mean reverting. Given this, in order to develop a more robust pairs-trading strategy using mean reversion techniques, cointegration needs to be created or found within the assets time series instead of finding time series that cointegrates.

Cointegration can be formed, so to say, if there is a linear combination of variables from a group of non-stationary time series variables. In other words, and as Longmore

(2016) points out, a mean reverting time series can be built using the adequate combination of non-stationary time series. An example of this is exploiting profit using such a technique in a portfolio that is composed of assets where the sum of the market value is a stationary time series. A portfolio can be exploited with a mean-reversion strategy, regardless of the fact that the assets alone are not mean reverting. Simply put, the suitable allocation of capital to each asset in the respective position can achieve such desired outcome. (Longmore 2016)

In order to formulate a cointegrating portfolio, first the assets need to be selected and then the appropriate hedge ratios, or coefficients, need to be calculated. LTC and BTC are the start but to fill out the portfolio, a fiat currency is added. In this example, the pairs are BTC/USD, LTC/USD and LTC/BTC as these are pairs that are available in the region. Once the assets have been selected the next step is to calculate the hedge ratios. In order to do so the Johansen Test for cointegration of time series is applied. The test result will be later used in the trading strategy. The Johansen test is explained by Gerald Dwyer as the following, "The Johansen test can be seen as a multivariate generalization of the augmented Dickey-Fuller test. The generalization is the examination of linear combinations of variables for unit roots. The Johansen test and estimation strategy – maximum likelihood – makes it possible to estimate all cointegrating vectors when there are more than two variables." (Dwyer 2015 pg 1) In the case of the assets chosen, there is more than one variable and using these cointegrating vectors, the mean reverting portfolio is calculated. Applying the Johansen Test for BTC/USD, LTC/USD and LTC/BTC the following results are reached:

```
######################
# Johansen-Procedure #
######################

Test type: trace statistic, with linear trend

Eigenvalues (lambda):
[1] 0.061903386 0.014759593 0.007041247

Values of test statistic and critical values of test:

          test 10pct  5pct  1pct
r <= 2 |  2.06  6.50  8.18 11.65
r <= 1 |  6.38 15.66 17.95 23.52
r = 0  | 24.98 28.71 31.52 37.22

Eigenvectors, normalised to first column:
(These are the cointegration relations)

                BTCUSD.Close.l2 LTCUSD.Close.l2 LTCBTC.Close.l2
BTCUSD.Close.l2        1.000000       1.0000000         1.00000
LTCUSD.Close.l2      -56.945119       0.3367375       -58.21229
LTCBTC.Close.l2       -2.278761      31.8858749      -161.66769

Weights W:
(This is the loading matrix)

               BTCUSD.Close.l2 LTCUSD.Close.l2 LTCBTC.Close.l2
BTCUSD.Close.d    0.0928274737   -1.180255e-02   -8.767668e-05
LTCUSD.Close.d    0.0030705206   -4.415263e-05   -6.325565e-06
LTCBTC.Close.d   -0.0007006162   -6.798526e-05    6.705615e-05
```

Note. Johansen Test Result for BTC/USD, LTC/USD, and LTC/BTC produced in program R.

Fittingly, the eigenvectors are used as the hedge ratios of discrete price series to formulate a stationary portfolio. The Eigenvectors, which are the cointegration relations for the assets are calculated at BTC/USD = 1, LTC/USD = -56.95, and LTC/BTC = -2.28. These

values will be used in the trading strategy along with the half-life calculated at 12.8 by regressing the results on the lag period. The half-life for the portfolio is calculated the same way it was calculated for the LTC/BTC and used in a similar fashion as a variable for the strategy implementation.

4. RESULTS OF STRATEGIES

4.1. LINEAR MEAN REVERSION OF LTC/BTC

A rudimentary linear mean reverting strategy can be implemented by determining the normalized deviation of price from its moving average. In essence, this is a moving Z-score of the previous end of day price and as such, holding a position negatively proportional to the deviation. The lookback period, a period which defines when the model is formulated, is set to the half-life of mean reversion for both the moving average and the moving standard deviation. The standard deviation and the average are put as moving because as the behavior of the price series evolves over time, it will require the necessary adjustments provided.

In order to visual and measure the effectiveness of the proposed trading strategy, and automated trading program, Zorro, is used. Zorro allows a trading strategy to be coded, back tested, optimized, and trading in both demo and live settings. In this instance, Zorro will be used to test the success of the trading strategies on the LTC/BTC pair. The following Zorro code below implements the linear mean reversion strategy adapted for LTC/BTC. The number of asset lots held is equal to the negative of value of the Z-score. Essentially, this accounts for the fact that a Z-score greater than zero points to a downwards reversion and Z-score less than zero points to a positive reversion.

```
int lotsOpen() {
	string CurrentAsset = Asset;
	int val = 0;
	for(open_trades)
	if(strstr(Asset,CurrentAsset) && TradeIsOpen)
	val += TradeLots;
```

```
	return val;
}

function run() {
	set(LOGFILE);
	BarPeriod = 1440;
	StartDate = 20170101;
	EndDate = 20180505;
	Spread = 	Slippage = RollShort = RollLong = 0;
	PlotWidth = 750;

	int halfLife = 50.4;
	LookBack = halfLife+1;

	vars Close = series(priceClose());
	vars zScore = series(10*(-(Close[0] - SMA(Close, halfLife))/StdDev(Close,
halfLife))); // multiply by 10 as minimum lot size is 1
	int openLots;

	vars ma = series(SMA(Close, halfLife));
	vars delta = series(100 *(ma[0] - ma[1]));
	var threshold = .07; //0.045

#ifdef USEFILTER
if (abs(delta[0]) < threshold) {

	if (zScore[0] > 0) { //want to be long the asset
		exitShort();
		openLots = lotsOpen();
		if (openLots < zScore[0]) {//need to buy more
			Lots = zScore[0] - openLots;
			enterLong();
			}
		else if (openLots > zScore[0]) {
			exitLong(0,0,(openLots - zScore[0])); //need to close some
			}
	}
	else if (zScore[0] < 0) { //want to be short the asset
		exitLong();
		openLots = lotsOpen();
		if (openLots < abs(zScore[0])) { //need to sell more
			Lots = abs(zScore[0]) - openLots;
			enterShort();
```

```
				}
			else if (openLots > abs(zScore[0])) {
				exitShort(0,0,(openLots - abs(zScore[0])));
				}
		}
}
else if (abs(delta[0]) > threshold) { // exit open trades if rate of change exceeds
threshold
		exitLong("*"); exitShort("*");
}

#else

if (zScore[0] > 0) { //want to be long the asset
			exitShort();
			openLots = lotsOpen();
			if (openLots < zScore[0]) {//need to buy more
				Lots = zScore[0] - openLots;
				enterLong();
				}
			else if (openLots > zScore[0]) {
				exitLong(0,0,(openLots - zScore[0])); //need to close some
				}
		}
		else if (zScore[0] < 0) { //want to be short the asset
			exitLong();
			openLots = lotsOpen();
			if (openLots < abs(zScore[0])) { //need to sell more
				Lots = abs(zScore[0]) - openLots;
				enterShort();
				}
			else if (openLots > abs(zScore[0])) {
				exitShort(0,0,(openLots - abs(zScore[0])));
				}
		}

#endif

		plot("zScore", zScore, NEW, BLUE);
		plot("MAve", SMA(Close, halfLife), NEW, GREEN);
		plot("MSD", StdDev(Close, halfLife), NEW, RED);
		plot("delta", delta, NEW, BLUE);
```

Note. Code adapted from Longmore (2015) Linear Mean Reversion Strategy with variables calculated in this study and standard Lite-c commands in Zorro.

The strategy as tested on the LTC/BTC for the period of January, 2017 until May, 2018 returns a meager 4.9% per year. The win percentage of the 288 trades is 59.5% with a Sharpe Ratio of 0.21. The gains are not that impressive considering the overall growth over the market during the same time period.

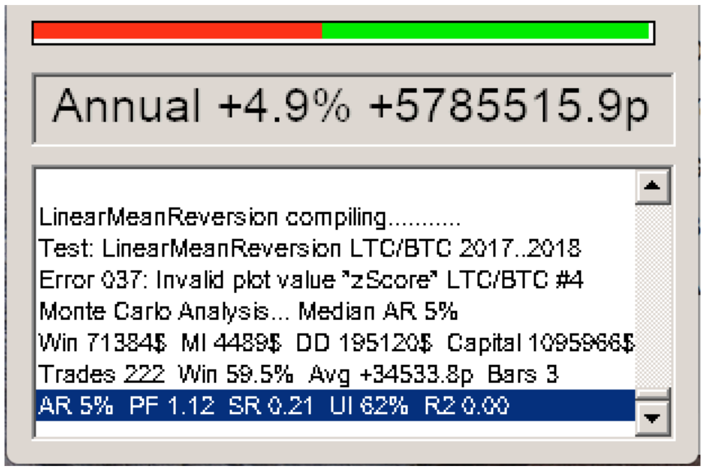

Figure 5. Back test result for Linear Mean Reversion LTC/BTC strategy applied for period Jan. 2017- May. 2018. Data results from strategy coded in Lite-C and back tested in trading program Zorro.

The graph below depicts the win/loss visualization of all the trades and the equity curve, both plotted throughout the time frame that the strategy is applied. Furthermore, The Z-score is plotted in blue, the SMA in green, the Moving Standard Deviation in red and the Delta again in blue.

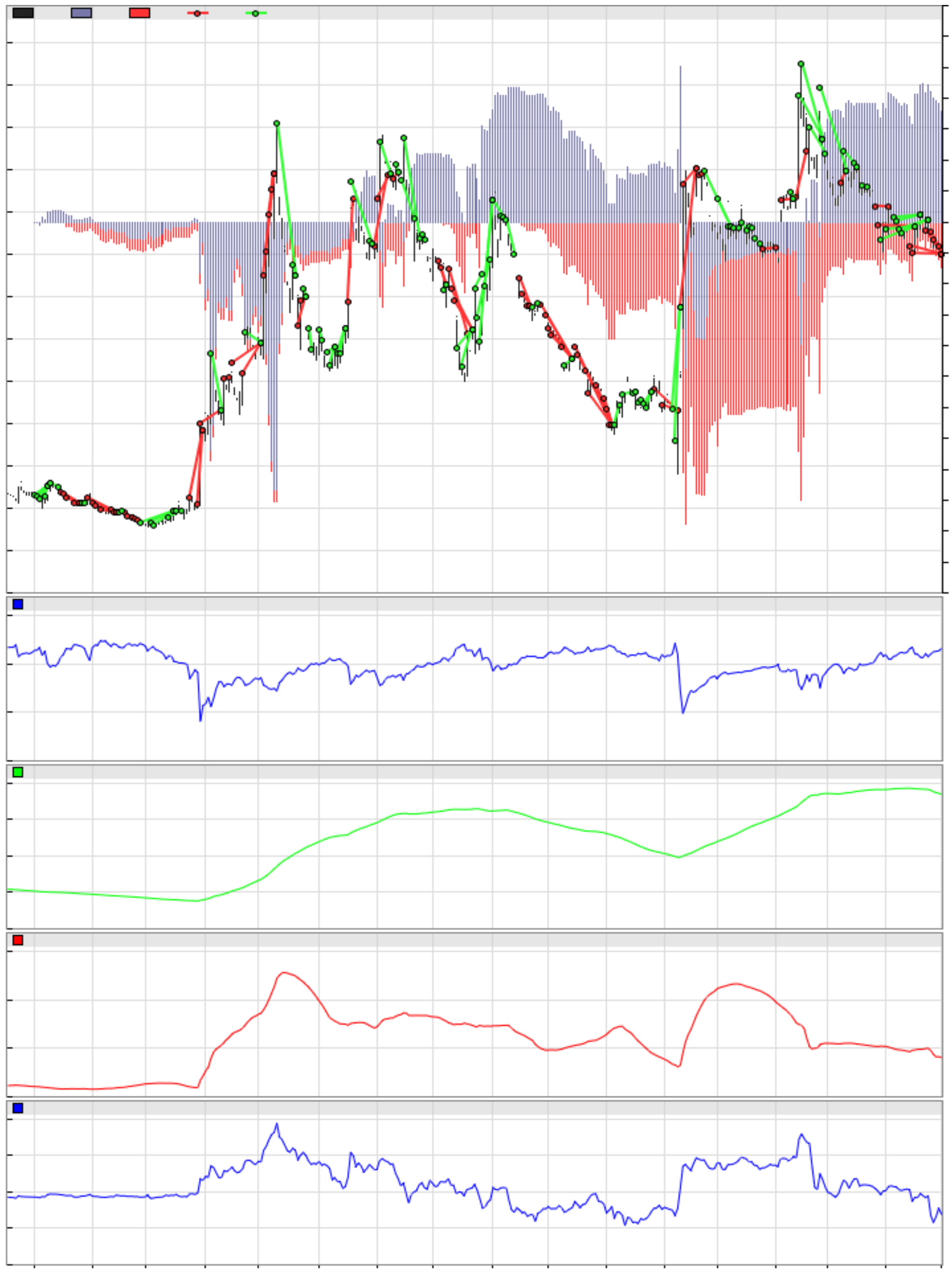

Figure 6. Graphical result for Linear Mean Reversion LTC/BTC strategy applied for period Jan. 2017- May. 2018. The win/loss and equity curve are displayed in the first portion of the graphic. The Z-score is plotted in blue, the SMA in green, the Moving Standard Deviation in red and the Delta again in blue. Data results from strategy coded in Lite-C and back tested in trading program Zorro.

The strategy faced difficult in trading with the price direction during both bullish and bearish periods. A considerable amount of trades took place in the back test, but very little in terms of profit was achieved for all the effort. In order to further pursue the idea of linear mean reversion type strategies, a more robust, cointegrated portfolio approach is considered.

4.2. COINTEGRATING PORTFOLIO - LINEAR MEAN REVERSION

A more complex linear mean reverting strategy can be implemented along similar lines as the previous strategy. However, the strategy is applied on the portfolio holding a weighted position in the three different assets proportional to the deviation. The lookback period is also used in the same way and is set to the half-life of mean reversion of 12.8 days for both the moving average and the moving standard deviation. The standard deviation and the average are put as moving because as the behavior of the price series evolves over time, it will require the necessary adjustments provided. The following Zorro code below implements the linear mean reversion strategy for cointegration portfolio adapted for BTC/USD, LTC/USD, and LTC/BTC.

```
int lotsOpen() {
        string CurrentAsset = Asset; // Asset is changed in the for loop
        int val = 0;
        for(open_trades)
        if(strstr(Asset,CurrentAsset) && TradeIsOpen)
        val += TradeLots;
        return val;
}

function run() {
        set(LOGFILE|PARAMETERS);
        BarPeriod = 1440;
        StartDate = 2017;
        EndDate = 20180501;

```

```
TradesPerBar = 3;
PlotWidth = 650;

int halfLife = 12.8;
LookBack = halfLife+1;

var BetaY = 1.0;
var BetaX = -56.95;
var BetaZ = -2.28;
string asset_y = "BTC/USD";
string asset_x = "LTC/USD";
string asset_z = "LTC/BTC";
asset(asset_y);
Spread =        Slippage = RollShort = RollLong = 0;
vars y = series(priceClose());
asset(asset_x);
Spread =        Slippage = RollShort = RollLong = 0;
vars x = series(priceClose());
asset(asset_z);
Spread =        Slippage = RollShort = RollLong = 0;
vars z = series(1/priceClose());

vars sprd = series(BetaY*y[0] + BetaX*x[0] + BetaZ*z[0]);
vars zScore = series(-(sprd[0] - SMA(sprd, halfLife))/StdDev(sprd, halfLife));

var posValY = 100*BetaY*zScore[0];
var posValX = 100*BetaX*zScore[0];
var posValZ = 100*BetaZ*zScore[0];

int targetLots_y = posValY;
int targetLots_x = posValX;
int targetLots_z = posValZ;

asset(asset_y);
int lotsOpen_y;

if (targetLots_y > 0) { //want to be long asset_y
	exitShort();
	lotsOpen_y = lotsOpen();
	if (lotsOpen_y < targetLots_y) {//need to buy more y
		Lots = targetLots_y - lotsOpen_y;
		enterLong();
		}
```

```
			else if (lotsOpen_y > targetLots_y) {
				exitLong(0,0,(lotsOpen_y - targetLots_y)); //need to close some y
				}
		}
		else if (targetLots_y < 0) { //want to be short asset_y
			exitLong();
			lotsOpen_y = lotsOpen();
			if (lotsOpen_y < abs(targetLots_y)) { //need to sell more y
				Lots = abs(targetLots_y) - lotsOpen_y;
				enterShort();
				}
			else if (lotsOpen_y > abs(targetLots_y)) {
				exitShort(0,0,(lotsOpen_y - abs(targetLots_y)));
				}
		}

		asset(asset_x);
		int lotsOpen_x;
		if (targetLots_x > 0) { //want to be long asset_x
			exitShort();
			lotsOpen_x = lotsOpen();
			if (lotsOpen_x < targetLots_x) { //need to buy more x
				Lots = targetLots_x - lotsOpen_x;
				enterLong();
			}
			else if (lotsOpen_x > targetLots_x) exitLong(0,0,(lotsOpen_x-targetLots_x));
		}
		else if (targetLots_x < 0) { //want to be short asset_x
			exitLong();
			lotsOpen_x = lotsOpen();
			if (lotsOpen_x < abs(targetLots_x)) { //need to sell more x
				Lots = abs(targetLots_x) - lotsOpen_x;
				enterShort();
			}
			else if (lotsOpen_x > abs(targetLots_x)) exitShort(0,0,(lotsOpen_x - abs(targetLots_x)));
		}

		asset(asset_z);
		int lotsOpen_z;
		if (targetLots_z > 0) { //want to be long asset_z
```

```
			exitLong();
			lotsOpen_z = lotsOpen();
			if (lotsOpen_z < targetLots_z) { //need to buy more z
				Lots = targetLots_z - lotsOpen_z;
				enterShort();
			}
			else if (lotsOpen_z > targetLots_z) exitShort(0,0,(lotsOpen_z-
targetLots_z));
		}
		else if (targetLots_z < 0) { //want to be short asset_z
			exitShort();
			lotsOpen_z = lotsOpen();
			if (lotsOpen_z < abs(targetLots_z)) { //need to sell more z
				Lots = abs(targetLots_z) - lotsOpen_z;
				enterLong();
			}
			else if (lotsOpen_z > abs(targetLots_z)) exitLong(0,0,(lotsOpen_z -
abs(targetLots_z)));
		}

		lotsOpen_z = lotsOpen();
		asset(asset_x);
		lotsOpen_x = lotsOpen();
		asset(asset_y);
		lotsOpen_y = lotsOpen();
		if (lotsOpen_y != abs(targetLots_y) or lotsOpen_x != abs(targetLots_x) or
lotsOpen_z != abs(argetLots_z))
		printf("something is wrong: lots open is not equal to target lots");

		PlotHeight2 = 200;
		ColorUp = ColorDn = ColorWin = ColorLoss = 0;
		plot("sprd", sprd, MAIN, BLACK);
		plot("zScore", zScore, NEW, RED);

```

Note. Code adapted from Longmore (2016) Linear Mean Reversion Strategy with variables calculated in this study and standard Lite-c commands in Zorro.

The strategy as tested on the portfolio for the period of January, 2017 until May, 2018 returns a low 9.7% per year. The win percentage of the 588 trades is 53% with a Sharpe Ratio of 0.40. The strategy performed better than the more basic linear mean reversion strategy but still these gains are not that impressive when considering the overall growth over the market during the same time period. The results are below in Figure 6.

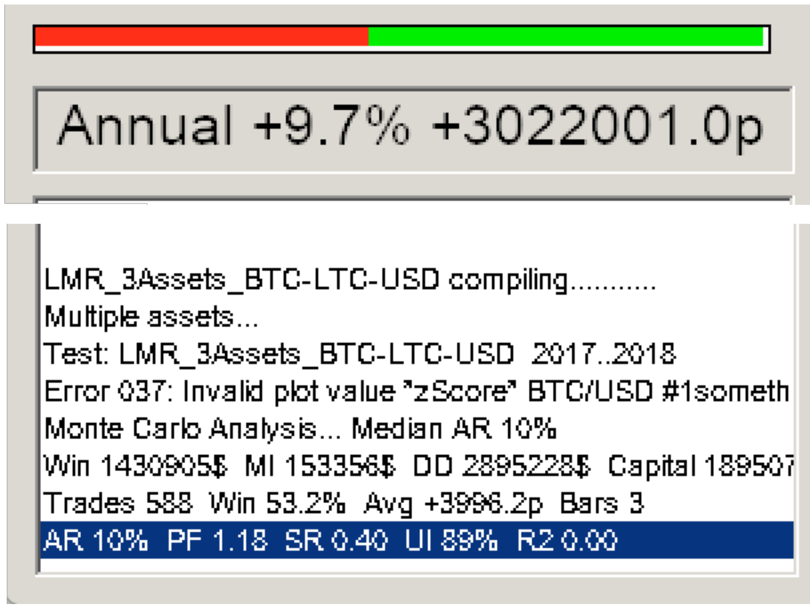

Figure 6. Back test result for Cointegrating Portfolio Linear Mean Reversion BTC/USD, LTC/USD, and LTC/BTC strategy applied for period Jan. 2017- May. 2018. Data results from strategy coded in Lite-C and back tested in trading program Zorro.

The graph below depicts the win/loss visualization of all the trades and the equity curve, both plotted throughout the time frame that the strategy is applied. Furthermore, The Z-score is plotted in red.

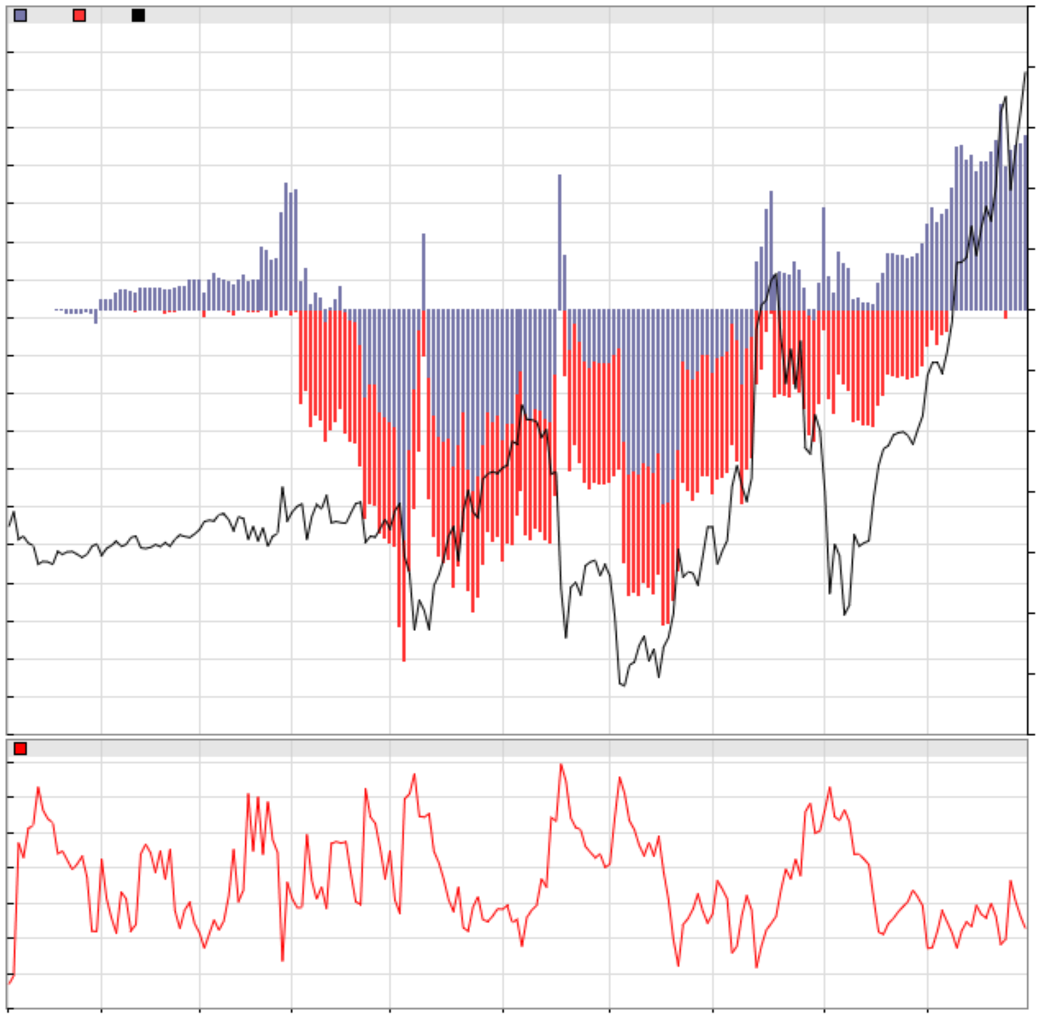

Figure 8. Graphic result for Cointegrating Portfolio Linear Mean Reversion BTC/USD, LTC/USD, and LTC/BTC strategy applied for period Jan. 2017- May. 2018. The win/loss and equity curve are displayed in the first portion of the graphic. The Z-score is plotted in red.

The strategy performed poorly and only returned to profit towards the end of the trading time range. The strategy also requires significant amount of trades, 588, to rebalance the portfolio. Luckily with digital assets, fractions can be bought which reduces the total size of the rebalancing but in most exchanges, fees will be applied which are not considered in this test, making the strategy less advantageous. In order to further pursue the idea of linear mean reversion type strategies, a simpler approach is considered.

4.3. BOLLINGER BAND

There are other technical analysis indicators that can aide in trade strategy formulation based on what is seen in the behavior of the assets. Continuing along the lines of the LTC/BTC mean reversion, Bollinger Bands can be used to try and implement similar strategy. Bollinger Bands are drawn two standard deviations away from the simple moving average, which varies depending on the time scale. As John Bollinger himself explains the concept: “Bollinger Bands define high and low on a relative basis. By definition prices are high at the upper band and low at the lower band.” (John Bollinger @bbands twitter.com/bbands). The concept fits closely with the previous linear mean reversion strategy. Basically, a strategy can be formulated on the degree of price movement reversion based on the, in this case, Bollinger bands. The strategy would trade when the price passes the upper or lower band, betting that it will revert back to the SMA mid-line. It’s assumed that price movement outside of the Bollinger bands is abnormal and inside is normal, profiting on these reoccurring abnormal to normal price reversions. The following figures show the code for the strategy and the back tested result for the trading period.

```
int lotsOpen() {
          function run()
{

  set(LOGFILE);
  BarPeriod = 1440;
  StartDate = 20170101;
  EndDate = 20180505;
  PlotWidth = 750;


  vars Close = series(priceClose());

  int bbPeriod = 18;
  var bbSD = 2;
  BBands(Close, bbPeriod, bbSD, bbSD, MAType_EMA);
```

```

  Stop = 2*ATR(25);
  TakeProfit = rRealMiddleBand; // exit at middle band value at trade entry

  if(crossOver(Close, rRealUpperBand))
  {
    reverseShort(1);
  }

  if(crossUnder(Close, rRealLowerBand))
  {
    reverseLong(1);
  }

  plot("upperBB", rRealUpperBand, BAND1, YELLOW);
  plot("lowerBB", rRealLowerBand, BAND2, YELLOW+TRANSP);
  plot("middleBB", rRealMiddleBand, MAIN, BLUE);
}
```

Note. Code compiled from standard lite-c commands in Zorro.

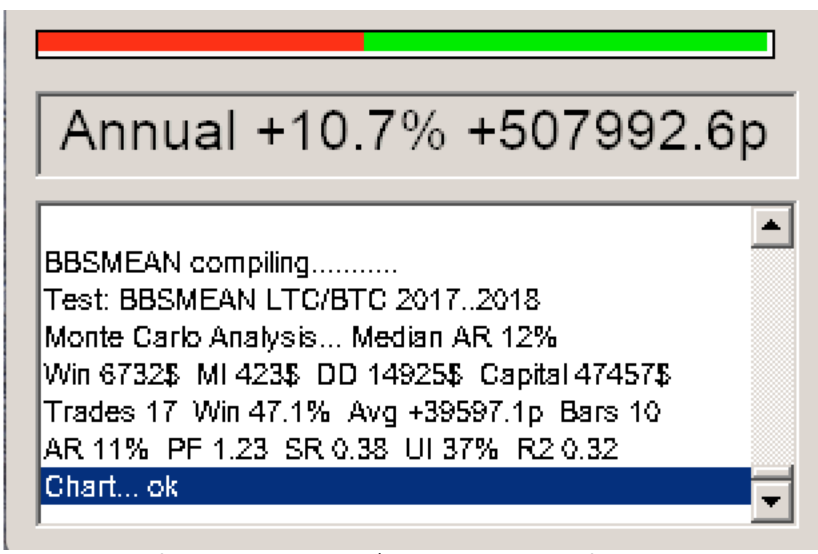

Figure 9. Back test result for Bollinger Band LTC/BTC strategy applied for period Jan. 2017- May. 2018. Data results from strategy coded in Lite-C and back tested in trading program Zorro.

The code plots the SMA and Bollinger bands on the daily time frame with an 18-day Bollinger Band period and two standard deviations from the moving average as a trade trigger. The result is not so profitable, only returning only 10.7% The win percentage of the 17 trades is 47.1% with a Sharpe Ratio of 1.23.

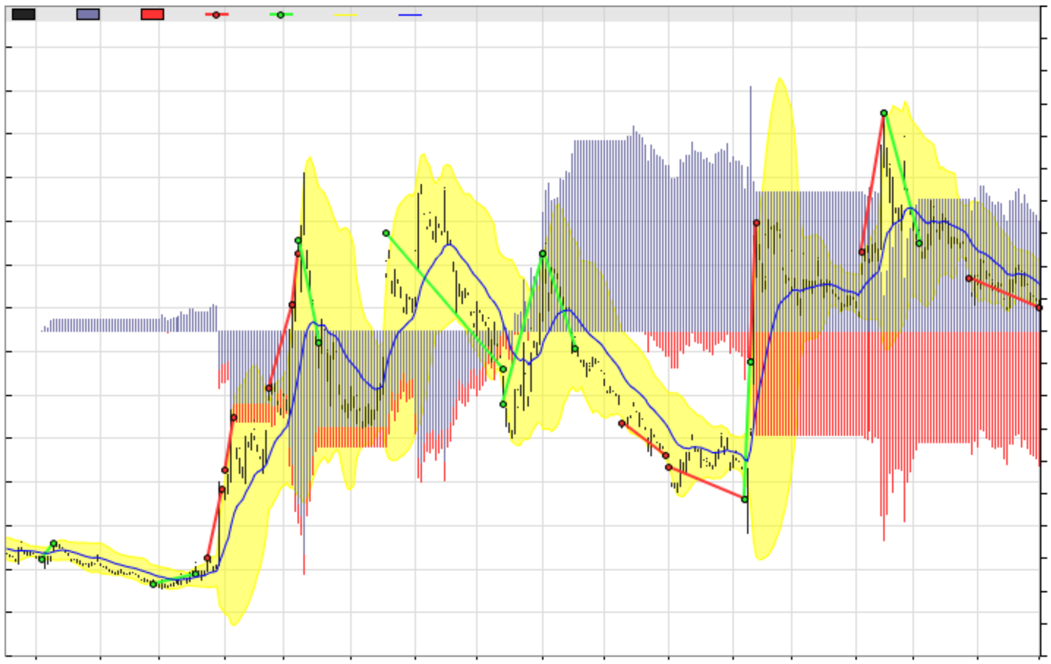

Figure 10. Graphic result for Bollinger Band LTC/BTC strategy applied for period Jan. 2017- May. 2018. The win/loss and equity curve are displayed in the first portion of the graphic.

Examining the win/loss and equity curve, it's clear that the strategy had trouble performing during bullish periods but was able to trade well when price movement turned bearish. To take advantage of such general price direction as opposed to betting against, the notion of moving averages can be taken from the Bollinger Bang strategy and used to build another.

4.4. EXPONENTIAL MOVING AVERAGES

Moving averages can be used to form the base of strategies. Employing moving averages in strategies aims at determining bullish or bearish price direction, and trading based on what general direction the moving averages point to. Moving averages can be adjusted between higher or lower to trade on either macro or micro levels. SMA can be used but so can the Exponential Moving Average (EMA). EMA, as the name suggest, is an exponential moving average, and gives higher weight to the more recent days in the average period. In this sense, the EMA tries to improve on the SMA by getting a closer feeling the more recent days and therefore more accurately reflect the current trend and

price direction. In this strategy the EMA is utilized due to the speed and volatility for which the digital asset is known for. The following code and figures show the code for the strategy and the back tested result for the trading period:

```
function run() {

 set(LOGFILE);
            BarPeriod = 1440;
            StartDate = 20170101;
            EndDate = 20180505;
            Spread =          Slippage = RollShort = RollLong = 0;
            PlotWidth = 750;

 var *Price = series(price());
 var *EMA5 = series(EMA(Price,5));
 var *EMA10 = series(EMA(Price,10));
 var *RSI10 = series(RSI(Price,10));
  int crossed = 0;

 if(crossOver(EMA5,EMA10)) crossed = 1;
 else if(crossUnder(EMA5,EMA10)) crossed = -1;

 if(crossed == 1 && crossOver(RSI10,50))
                    enterLong();
 else if(crossed == -1 && crossUnder(RSI10,50))
                   enterShort();
}
```

Note. Code compiled from standard Lite-c commands in Zorro

The strategy is set to use the 5-day and 10-day EMA with an additional RSI used and indicator to determine when to trigger a trade. When the 5-day crosses the 10-day EMA going up, the sentiment is interpreted as bullish and the trade made will be long. Should the EMAs cross in the other direction, the opposite sentiment, bearish, is interpreted and a short trade is trigged.

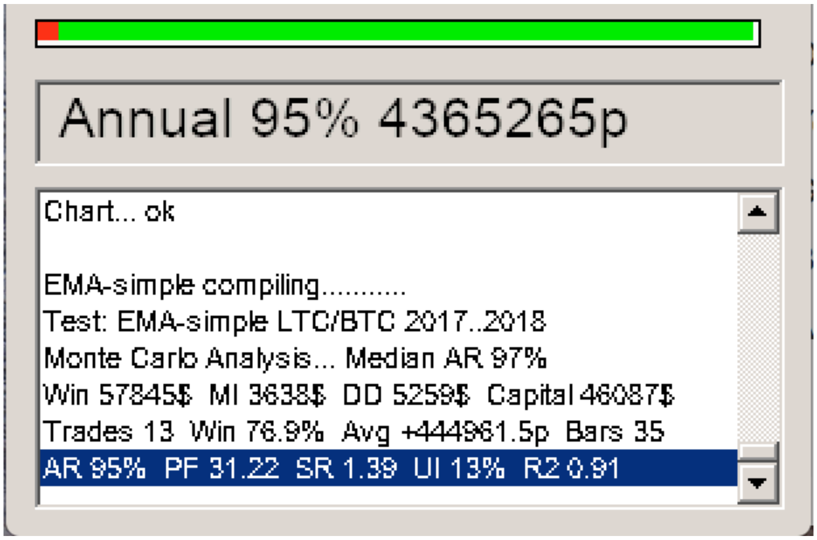

Figure 11. Back test result for EMA LTC/BTC strategy applied for period Jan. 2017- May. 2018. Data results from strategy coded in Lite-C and back tested in trading program Zorro.

The strategy provides a significant profit however very little trades are performed. The win percentage of the 13 trades is 76.9% with a Sharpe Ratio of 1.39. The trades were made profitable in both directions with only a few losing trades.

Figure 12. Graphic result for EMA LTC/BTC strategy applied for period Jan. 2017- May. 2018. The win/loss and equity curve are displayed in the first portion of the graphic.

The win/loss and equity curve look attractive, albeit meager, when compared to the previous two strategies. The trades are few, but profitable and the equity curve is positive for the near entirety of the back test.

4.5. MOMENTUM

A momentum trading strategy focuses on the speed of price movement. It aims to trade with the trend as it maintains direction and therefore profiting of the momentum of the asset's price movement. Momentum trading is effective when trading in volatile assets when there is the strategy seems fitting due to the high volatile of digital assets. The Mom function, Mom for momentum, is implemented in a trading strategy. The function comes out of the box from the Zorro software and is configured with a number of oscillators and parameters to determine moment. The following code and figures show the code for the strategy and the back tested result for the trading period:

```
function run()
{
	 set(LOGFILE);
	BarPeriod = 1440;
	StartDate = 20170101;
	EndDate = 20180505;
	Spread =          Slippage = RollShort = RollLong = 0;
	PlotWidth = 750;
	LookBack = 160;

	vars Close = series(priceClose());

	int Formation = 1;
	var AbsMom = Mom(Close, Formation);

	if(AbsMom > 0) reverseLong(1);
	if(AbsMom < 0) reverseShort(1);

	PlotWidth = 1200;
	PlotScale = 10;
	plot ("mom", AbsMom, NEW|BARS, BLUE);
}
```

Note. Code compiled from standard Lite-c commands in Zorro

The momentum index is used to judge the momentum of the current price movement and trade based on the trend. The period is set very shot to one day, again due to the volatile nature of the assets.

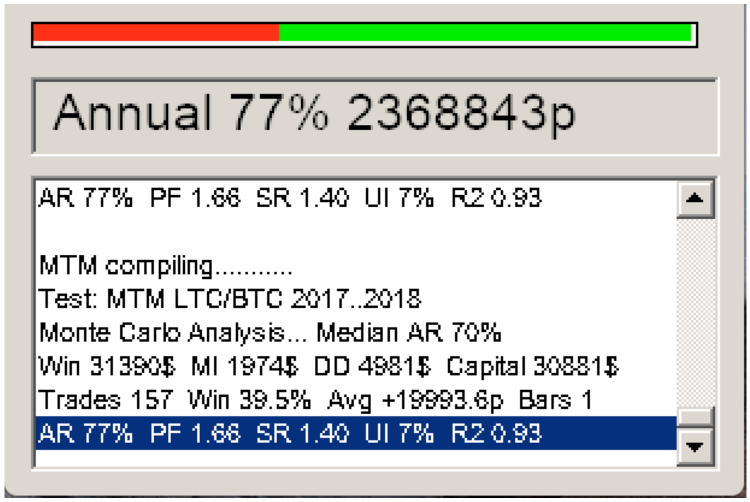

Figure 13. Graphic result for Momentum LTC/BTC strategy applied for period Jan. 2017- May. 2018 Data results from strategy coded in Lite-C and back tested in trading program Zorro.

The results are indeed impressive, with a return of 77% and a lot of trading action. The win percentage of the 157 trades is 39.5% with a Sharpe Ratio of 1.40. The momentum function appears to have grasped the sentiment of the price movement and made many trades trying to predict its path.

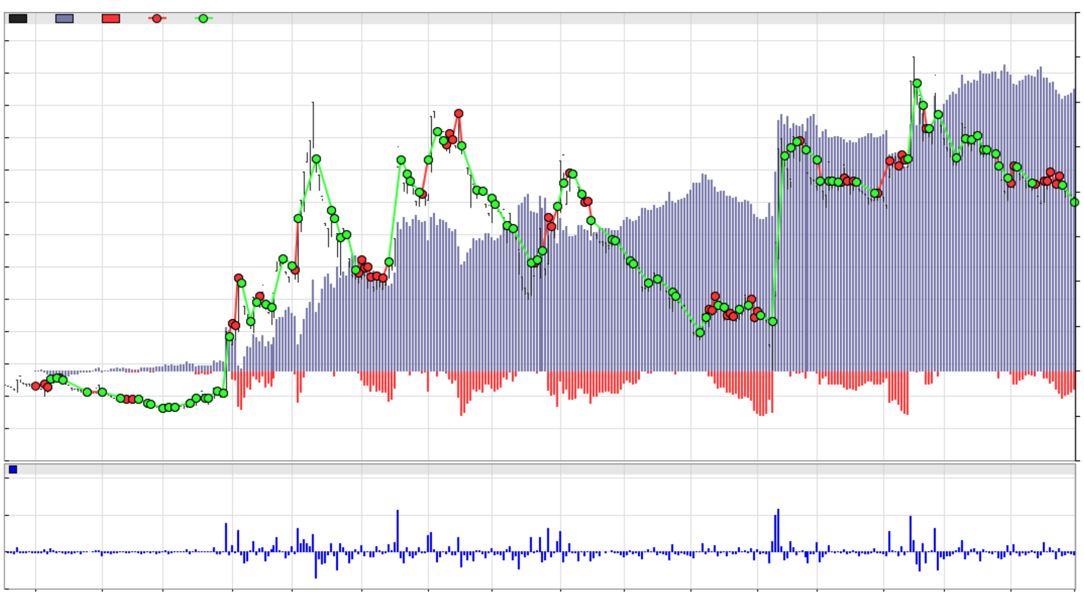

Figure 14. Graphic result for Momentum LTC/BTC strategy applied for period Jan. 2017- May. 2018. The win/loss and equity curve are displayed in the first portion of the graphic.

Looking at the equity curve it's evident that the strategy performed well in both directions of the market, executing many trades, and profiting of the price movement in both directions. The momentum strategy, even though it's not the most profitable present, shows promise as the it presents a model that profits from the price movement in both directions. The strategy trades successful as the price zigs and zigs back and both or reverts on itself as it trends in an upward motion. The momentum strategy successfully meets the objective of a responsive strategy that trades with the normal and abnormal movements of the ratio.

5. CONCLUSION

The main conclusion is that arbitrage in the digital asset market presents risks and rewards on a more complex level rather than assuming large inter-exchange spreads are given to low-effort low-risk profits. Chan (2013) challenges the use of statistical tests for stationarity give that the trader's overarching goal is only to discover whether a certain mean reversion strategy's performance meets a minimum threshold to trade. As it happens, the statistical significance of stationarity tests is usually far higher than that obtained through a simple back test. The explanation is that tests such as these make use of the data represented in the entire sample of the price series. In contrast, a back test works on the number of executed trades, which in most cases far less. Furthermore, the majority of strategies' potential is reliant on a set of constraints that are largely outside to the price series itself, which also mystifies the concept of statistical significance. However, when a price series meets the requirements set forth by statistical tests for stationarity, or results in a short enough half-life of mean reversion, it can be assumed that a profitable mean reversion strategy does in fact exist.

Exchange to exchange arbitrage is a viable method, however it's risk level is too high from some traders to bare. Therefore, Pairs Trading is a viable method at profiting from price discrepancies in the market without running the high costs and risks of long term investing or exchange to exchange arbitrage. The concepts shown in this study present

various degrees of profitability. Judging solely on the financial result, it could be argued that the momentum strategy is the most promising given the relatively high profit and high Sharpe ratio when compared to the rest of the approaches test. The strategies prove that profit is possible and that it can be a viable way to take advantage of the market. The strategies must be more robust should they be used in a live trading environment. In such cases, lower bar periods, or time scales, are appropriate as are trading strategies that depend on more variables, triggers, and checks. Equally important is the strategy's ability to adjust to the trend behavior of the asset pair. Optimizing a strategy for one period is not guarantee that it will be optimum going forward. Consequently, an ideal strategy is such that uses a balance of statistical and technical trading concepts along with constant adjustments to the current trend in pursuance of desired profits.

Works Cited

Athanasiadis, Theo. "Trend, Mean-Reversion or Random Walk? A Statistical Analysis of Price Behavior in Major Markets." *By John Cigno :: SSRN*, 2 May 2016, papers.ssrn.com/sol3/papers.cfm?abstract_id=2773302.

"The Bitcoin Volatility Index." *Bitcoin Volatility Index - Charts vs Dollar & More*, www.buybitcoinworldwide.com/volatility-index/.

"BTC BRL | Bitcoin Brazil Real MercadoBitcoin." *Investing.com*, www.investing.com/crypto/bitcoin/btc-brl.

"BTC USD | Bitcoin US Dollar BitStamp." *Investing.com*, www.investing.com/crypto/bitcoin/btc-usd?cid=49798.

Chan, Ernie. *Algorithmic Trading: Winning Strategies and Their Rationale*. John Wiley & Sons, 2013.

"Cryptocurrency Market Capitalizations." *CoinMarketCap*, coinmarketcap.com/.

"Cryptocurrency Transaction Speeds: The Complete Review." *The Daily Hodl*, 1 May 2018, dailyhodl.com/2018/04/27/cryptocurrency-transaction-speeds-the-complete-review/.

"Cryptowatch." *LTCBTC - Poloniex Live Chart - Cryptowatch*, cryptowat.ch/markets/poloniex/ltc/btc/3d.

Dwyer, Gerald. "The Johansen Tests for Cointegration." *Jerryddwyer.com*, Apr. 2015, www.jerrydwyer.com/pdf/Clemson/Cointegration.pdf.

"LTC BRL | Litecoin Brazil Real MercadoBitcoin." *Investing.com*, www.investing.com/crypto/litecoin/ltc-brl.

"LTC BTC | Litecoin Bitcoin Poloniex." *Investing.com*, www.investing.com/crypto/litecoin/ltc-btc.

"LTC USD | Litecoin US Dollar BitStamp." *Investing.com*, www.investing.com/crypto/litecoin/ltc-usd.

Longmore, Kris, et al. "Exploring Mean Reversion and Cointegration with Zorro and R: Part 1." *Robot Wealth*, 3 Dec. 2015, robotwealth.com/exploring-mean-reversion-and-cointegration-with-zorro-and-r-part-1/.

Longmore, Kris, et al. "Exploring Mean Reversion and Cointegration: Part 2." *Robot Wealth*, 2 Aug. 2016, robotwealth.com/exploring-mean-reversion-and-cointegration-part-2/.

Ramos-Requena, J.P., et al. "INTRODUCING HURST EXPONENT IN PAIR TRADING." *INTRODUCING HURST EXPONENT IN PAIR TRADING*, Departamento De Economía y Empresa, 3Departamento De Matemáticas - Universidad De Almería, 26 Nov. 2017, www.researchgate.net/publication/318385038_Introducing_Hurst_exponent_in_pair_trading.

Vidyamurthy, Ganapathy. *Pairs Trading: Quantitative Methods and Analysis*. J. Wiley, 2004.

Test Linear Mean Reversion LTC/BTC

Simulated account AssetsFix (NFA)
Bar period 24 hours (avg 2026 min)
Test period 2017-01-02..2018-05-01 (344 bars)
Lookback period 51 bars (10 weeks)
Montecarlo cycles 200
Simulation mode Realistic (slippage 0.0 sec)
Spread 0.0 pips (roll 0.00/0.00)
Commission 0.00
Contracts per lot 1.0

Gross win/loss 670240$ / -598856$ (+7666502p)
Average profit 53870$/year, 4489$/month, 207$/day
Max drawdown -195120$ 273.3% (MAE -195120$ 273.3%)
Total down time 89% (TAE 76%)
Max down time 17 weeks from Jan 2017
Max open margin 802380$
Max open risk 2012$
Trade volume 10730477$ (8097741$/year)
Transaction costs 0$ spr, 0$ slp, 0$ rol, -0.00$ com
Capital required 1095966$

Number of trades 222 (168/year, 4/week, 1/day)
Percent winning 59.5%
Max win/loss 64800$ / -105380$
Avg trade profit 322$ 34533.8p (+545321.1p / -714620.9p)
Avg trade slippage 0$ 0.0p (+0.0p / -0.0p)
Avg trade bars 3 (+1 / -3)
Max trade bars 13 (18 days)
Time in market 236%
Max open trades 9
Max loss streak 9 (uncorrelated 6)

Annual return 5%
Profit factor 1.12 (PRR 0.92)
Sharpe ratio 0.21
Kelly criterion 0.87
R2 coefficient 0.000
Ulcer index 62.1%

Confidence level AR DDMax Capital

10%	5%	140971	1014491$
20%	5%	158817	1041343$
30%	5%	170111	1058336$
40%	5%	184771	1080394$
50%	5%	205847	1112106$
60%	5%	234346	1154987$
70%	4%	264167	1199857$
80%	4%	339547	1313276$
90%	4%	405192	1412049$
95%	4%	488585	1537525$
100%	3%	791855	1993838$

Portfolio analysis	OptF	ProF	Win/Loss	Wgt%
LTC/BTC	.050	1.12	132/90	100.0
LTC/BTC:L	.004	1.31	57/53	57.9
LTC/BTC:S	.098	1.06	75/37	42.1

Test LMR – 3 Assets - BTC-LTC-USD

Simulated account   AssetsFix (NFA)
Bar period   24 hours (avg 2057 min)
Test period   2017-01-19..2017-10-30 (198 bars)
Lookback period   13 bars (18 days)
Montecarlo cycles   200
Simulation mode   Realistic (slippage 0.0 sec)

Gross win/loss   9545651$ / -8114746$ (+2349756p)
Average profit   1840275$/year, 153356$/month, 7078$/day
Max drawdown   -2895228$ 202.3% (MAE -2932803$ 205.0%)
Total down time   80% (TAE 88%)
Max down time   4 weeks from Mar 2017
Max open margin   13263771$
Max open risk   88938$
Trade volume   168385694$ (216559421$/year)
Transaction costs   0$ spr, 0$ slp, 0$ rol, -0.07$ com
Capital required   18950720$

Number of trades   588 (757/year, 15/week, 4/day)
Percent winning   53.2%
Max win/loss   1013820$ / -894040$
Avg trade profit   2434$ 3996.2p (+50081.0p / -48456.7p)
Avg trade slippage 0$ 0.0p (+0.0p / -0.0p)
Avg trade bars   3 (+2 / -1)
Max trade bars   12 (17 days)
Time in market   1058%
Max open trades   21
Max loss streak   6 (uncorrelated 9)

Annual return   10%
Profit factor   1.18 (PRR 1.05)
Sharpe ratio   0.40
Kelly criterion   1.76
R2 coefficient   0.000
Ulcer index   89.4%

Confidence level	AR	DDMax	Capital
10%	11%	1906999	17009592$
20%	10%	2201571	17588205$
30%	10%	2497992	18170451$

40%	10%	2752421	18670212$
50%	10%	3012165	19180414$
60%	9%	3489184	20117398$
70%	9%	3938675	21000311$
80%	8%	4474268	22052349$
90%	8%	5407589	23885623$
95%	7%	6170909	25384974$
100%	5%	11985971	36807205$

Portfolio analysis	OptF	ProF	Win/Loss	Wgt%
BTC/USD avg	.049	0.35	72/122	-0.4
LTC/BTC avg	.396	1.16	112/84	85.2
LTC/USD avg	.499	1.49	129/69	15.2
BTC/USD	.000	0.35	72/122	-0.4
BTC/USD:L	.098	1.84	49/25	0.1
BTC/USD:S	.000	0.13	23/97	-0.5
LTC/BTC	.186	1.16	112/84	85.2
LTC/BTC:L	.002	1.02	28/47	4.8
LTC/BTC:S	.791	1.32	84/37	80.3
LTC/USD	.999	1.49	129/69	15.2
LTC/USD:L	.999	5.15	87/36	26.2
LTC/USD:S	.000	0.56	42/33	-10.9

Test BBSMEAN LTC/BTC

Simulated account   AssetsFix (NFA)
Bar period   24 hours (avg 2029 min)
Test period   2017-01-02..2018-05-01 (344 bars)
Lookback period   80 bars (16 weeks)
Montecarlo cycles   200
Simulation mode   Realistic (slippage 5.0 sec)
Spread   0.0 pips (roll 0.00/0.00)
Commission   0.00
Contracts per lot   1.0

Gross win/loss   35785$ / -29053$ (+673151p)
Average profit   5080$/year, 423$/month, 19.54$/day
Max drawdown   -14925$ 221.7% (MAE -15327$ 227.7%)
Total down time   71% (TAE 50%)
Max down time   9 weeks from Dec 2017
Max open margin   25000$
Max open risk   2322$
Trade volume   218895$ (165188$/year)
Transaction costs   0$ spr, 1.05$ slp, 0$ rol, -0.00$ com
Capital required   47457$

Number of trades   17 (13/year, 1/week, 1/day)
Percent winning   47.1%
Max win/loss   6961$ / -6442$
Avg trade profit   396$ 39597.1p (+447309.9p / -322814.2p)
Avg trade slippage 0.06$ 6.2p (+2195.0p / -1939.4p)
Avg trade bars   10 (+12 / -9)
Max trade bars   39 (8 weeks)
Time in market   53%
Max open trades   1
Max loss streak   4 (uncorrelated 5)

Annual return   11%
Profit factor   1.23 (PRR 0.60)
Sharpe ratio   0.38
Kelly criterion   1.25
R2 coefficient   0.321
Ulcer index   36.6%

Confidence level   AR   DDMax Capital

10%	13%	9490	39279$
20%	12%	10481	40770$
30%	12%	11215	41875$
40%	12%	11836	42809$
50%	12%	12534	43860$
60%	11%	13415	45185$
70%	11%	14717	47144$
80%	10%	16042	49138$
90%	10%	18428	52728$
95%	9%	22549	58929$
100%	7%	31734	72749$

Portfolio analysis	OptF	ProF	Win/Loss	Wgt%
LTC/BTC	.344	1.23	8/9	100.0
LTC/BTC:L	.999	3.31	4/3	149.9
LTC/BTC:S	.000	0.86	4/6	-49.9

Test EMA-simple LTC/BTC

Simulated account AssetsFix (NFA)
Bar period 24 hours (avg 2029 min)
Test period 2017-01-02..2018-05-01 (344 bars)
Lookback period 80 bars (16 weeks)
Montecarlo cycles 200
Simulation mode Realistic (slippage 0.0 sec)
Spread 0.0 pips (roll 0.00/0.00)
Commission 0.00
Contracts per lot 1.0

Gross win/loss 59759$ / -1914$ (+5784499p)
Average profit 43653$/year, 3638$/month, 168$/day
Max drawdown -5259$ 9.1% (MAE -17223$ 29.8%)
Total down time 29% (TAE 90%)
Max down time 8 weeks from Jan 2017
Max open margin 38174$
Max open risk 382$
Trade volume 181071$ (136645$/year)
Transaction costs 0$ spr, 0$ slp, 0$ rol, -0.00$ com
Capital required 46087$

Number of trades 13 (10/year, 1/week, 1/day)
Percent winning 76.9%
Max win/loss 10809$ / -1343$
Avg trade profit 4450$ 444961.5p (+597590.0p / -63800.1p)
Avg trade slippage 0$ 0.0p (+0.0p / -0.0p)
Avg trade bars 35 (+43 / -7)
Max trade bars 90 (18 weeks)
Time in market 133%
Max open trades 3
Max loss streak 2 (uncorrelated 2)

Annual return 95%
Profit factor 31.22 (PRR 13.53)
Sharpe ratio 1.39
Kelly criterion 2.04
R2 coefficient 0.907
Ulcer index 13.5%

Confidence level AR DDMax Capital

10%	103%	2902	42540$
20%	100%	3687	43722$
30%	99%	4075	44306$
40%	98%	4320	44674$
50%	97%	4611	45112$
60%	96%	4954	45628$
70%	94%	5387	46279$
80%	92%	6085	47330$
90%	86%	8207	50522$
95%	84%	9171	51973$
100%	63%	20885	69599$

Portfolio analysis	OptF	ProF	Win/Loss	Wgt%
LTC/BTC	.999	31.22	10/3	100.0
LTC/BTC:L	.999	30.59	6/2	78.9
LTC/BTC:S	.999	33.85	4/1	21.1

Test MTM LTC/BTC

Simulated account   AssetsFix (NFA)
Bar period   24 hours (avg 2026 min)
Test period   2017-01-02..2018-05-01 (344 bars)
Lookback period   160 bars (33 weeks)
Montecarlo cycles   200
Simulation mode   Realistic (slippage 0.0 sec)
Spread   0.0 pips (roll 0.00/0.00)
Commission   0.00
Contracts per lot   1.0

Gross win/loss   78750$ / -47360$ (+3139001p)
Average profit   23688$/year, 1974$/month, 91.11$/day
Max drawdown   -4981$ 15.9% (MAE -5918$ 18.9%)
Total down time   62% (TAE 84%)
Max down time   8 weeks from Dec 2017
Max open margin   23386$
Max open risk   234$
Trade volume   2100998$ (1585516$/year)
Transaction costs   0$ spr, 0$ slp, 0$ rol, -0.00$ com
Capital required   30881$

Number of trades   157 (119/year, 3/week, 1/day)
Percent winning   39.5%
Max win/loss   10280$ / -3210$
Avg trade profit   200$ 19993.6p (+127016.1p / -49852.6p)
Avg trade slippage   0$ 0.0p (+0.0p / -0.0p)
Avg trade bars   1 (+2 / -1)
Max trade bars   7 (7 days)
Time in market   75%
Max open trades   1
Max loss streak   8 (uncorrelated 11)

Annual return   77%
Profit factor   1.66 (PRR 1.32)
Sharpe ratio   1.40
Kelly criterion   2.60
R2 coefficient   0.931
Ulcer index   6.6%

Confidence level   AR   DDMax Capital

10%	78%	4652	30385$
20%	75%	5398	31509$
30%	73%	5948	32336$
40%	72%	6463	33111$
50%	70%	7016	33943$
60%	67%	7828	35165$
70%	65%	8842	36690$
80%	61%	10312	38902$
90%	57%	12082	41565$
95%	53%	14107	44612$
100%	38%	25488	61737$

Portfolio analysis	OptF	ProF	Win/Loss	Wgt%
LTC/BTC	.999	1.66	62/95	100.0
LTC/BTC:L	.999	2.07	23/55	68.1
LTC/BTC:S	.999	1.36	39/40	31.9