Statistical Arbitrage in Cryptocurrency markets using principle components analysis

FNCE40003 Numerical Techniques in Finance
Major Assignment

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Contents

Abstract

Cryptocurrency is a relatively new asset class that has only recently begun to be integrated into modern financial markets. This paper employs a systematic technique first introduced in Avellaneda and Lee's 2010 paper *Statistical Arbitrage in the US Equities Market* to study statistical arbitrage in cryptocurrencies. Trading signals are generated through Principle Component Analysis. We decompose cryptocurrency returns into an idiosyncratic and systematic component, where the factors are derived from PCA. We assume mean reversion in the residual process, and model this process as an Ornstein-Uhlenbeck process based on Brownian motion. We find significant opportunity for such a statistical arbitrage strategy in cryptocurrency markets. The strategy delivers an in-sample Sharpe ratio of 5.29.

A brief introduction into cryptocurrencies

Blockchain

Cryptocurrency as an asset class as a whole is underpinned by blockchain technology. Blockchain is a relatively recent development, most famously introduced by Bitcoin creator Nakamoto (2009)[1]. The blockchain is a decentralised, distributed ledger, metaphorically a 'chain of blocks'. Each block in this chain stores information about a unique transaction – for example the time, the unique digital signatures of the participants in the transaction and a hash, a unique which serves as the identifier for that block. The blockchain is decentralised in the sense that the ledger exists in multiple locations simultaneously – hence it is stored in a distributed network. This ledger is public and available for anyone to observe.[2] In order for a block to be added to the chain, a transaction must occur, and this transaction must be verified. As opposed to a traditional financial intermediary, transactions are verified by the collective network. [3]

The verification process differs between mined and non-mined cryptocurrencies.[4] Mined cryptocurrencies operate on a 'proof-of-work' model. For mined cryptocurrencies such as Bitcoin, verification of a block occurs as other computers on the network solve complex mathematical equations; which form the basis of the encryption that protects transactions from hackers. These equations are integral in forming the 'secure' aspect of blockchain technology. Performing this validation is what is known as 'mining' in the cryptocurrency lexicon. Once a party (an individual, 'pool' or group of individuals) has successfully validated a block, they receive a 'block reward', paid out in the cryptocurrency that has been validate – validation of a block on the Bitcoin blockchain would be rewarded with bitcoin.

Non-mined currencies operate on a 'proof-of-stake' model. No complex equations or computing power is needed to validate transactions. Instead, a 'stake' in a cryptocurrency enables an individual to validate transactions. The larger the stake and the longer the duration of the holding, the more likely an individual is chosen to validate a block. Rather than being rewarded in newly 'mined' currency, the stakeholder receives the aggregate transaction fees from a block of transactions.

As a result of this technology, the marketplaces for digital assets such as Bitcoin benefit from increased competition, lower barriers to entry, speed, lower privacy risk and infrastructure supported by market participants independent to a platform operator (Catalini & Gans, 2017).

We refer to the following terms by the definition outlined below throughout the remainder of the paper.

[1] https://bitcoin.org/bitcoin.pdf
[2] https://www.blockchain.com/btc/blocks
[3] https://www2.deloitte.com/ch/en/pages/strategy-operations/articles/blockchain-explained.html
[4] https://www.fool.com/investing/2018/03/26/the-basics-of-mined-vs-non-mined-cryptocurrency-ex.aspx

Coin vs token

Within the broader asset class of cryptocurrencies there are a number of subclasses. We first make a distinction between 'coins' and 'tokens'. Coins are cryptocurrencies which have their own blockchain such as Bitcoin, or Ethereum. Tokens differ from traditional cryptocurrencies or 'coins' in that coins may operate independently whereas tokens depend on another cryptocurrency's blockchain as a platform to operate. ERC20 tokens are the most popular tokens and are created on the Ethereum platform. ERC20 tokens do not have their own blockchain and use Ethereum's. They behave in exactly the same way as traditional cryptocurrencies like Bitcoin, Litecoin, etc. They can have value, be sent and be received.

These tokens are floated to the market through an ICO, an initial coin offering – a form of capital raising for companies in the crypto-asset space where the company exchanges their token for at some rate for some existing currency. Hence, in addition to mining and purchasing them, another means of acquiring cryptocurrencies is through participation in ICOs. ICOs are unregulated and not well defined – there is no rule of thumb as to when and for how long it must take place. Investors in ICOs look to realise gains through the price of the tokens purchased increasing. Thanks to the ease of the Ethereum platform, tokens can be created in the span of minutes (Momtaz, 2019). 190,000 ERC20 tokens have been launched as of the time of writing.[5]

Stablecoin

Stablecoins are cryptocurrencies built to minimise the price volatility of the cryptocurrency relative to an asset or a basket of assets. They may be backed by currencies, assets (gold) or other cryptocurrencies. Examples are Tether (USDT), USD Coin (USDC), TrueUSD (TUSD) and Dai (DAI). Stablecoins are an incredibly recent development. As such, the empirical effects of having coins of such nature present in the cryptocurrency ecosystem are not well studied. Griffin and Shams (2018), find that Tether may be used to manipulate Bitcoin and other cryptocurrency price movements. In its relatively short lifespan, Tether has been the subject of much controversy. Tether's USD peg necessitates the presence of management, and actions by the company have come under scrutiny from the New York Attorney General's office.[6]

Altcoin

Any coin launched following Bitcoin is referred to as an altcoin. Hence, there is only one cryptocurrency that is not an altcoin – Bitcoin. Given this trivial definition, we will sparsely refer to altcoins in the paper.

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[5] https://etherscan.io/tokens

[6] https://www.forbes.com/sites/stevenehrlich/2019/05/02/after-an-850-million-controversy-what-everyone-should-know-about-bitfinex-tether-and-stablecoins/

Market Overview

Nonetheless, despite its infancy, cryptocurrency has become adopted as an asset class and widely traded. Exchanges such as Bitfinex, Binance and Kraken offer both retail and institutional investors alike to easily trade the currency on a platform that is familiar.

Cryptocurrency experienced one of the most spectacular bull runs in recent history during late 2017, as illustrated below by Figure 1, price series' for the four most prominent cryptocurrencies, Ripple, Bitcoin, Litecoin and Ethereum. This price surge was consistent throughout all coins – even lesser known niche coins and tokens. Things came to an end in early 2018. Prices tanked and liquidity across many already relatively illiquid altcoins crumbled as investors exited positions.

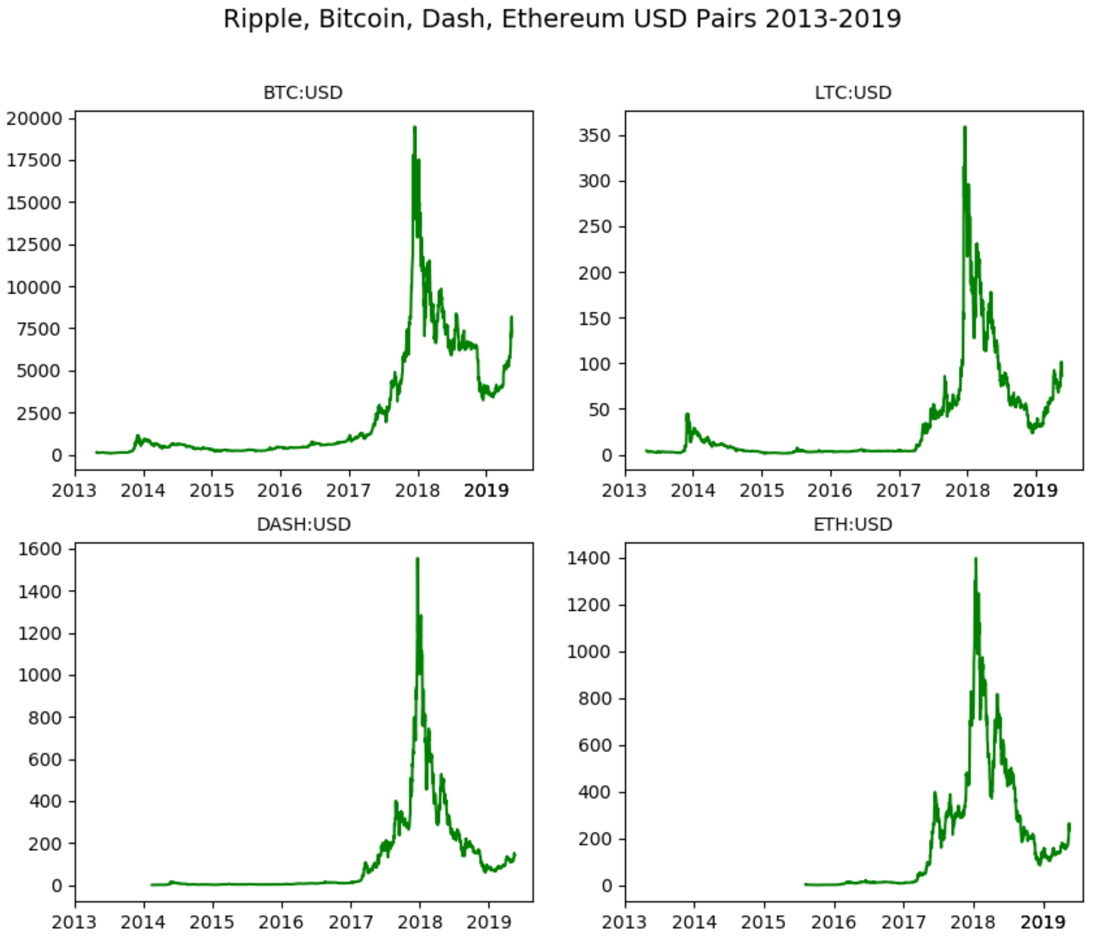

Figure 1 – *Daily closing prices of BTC, LTC, DASH and ETH to USD Pairs*

Q1 2019 saw a price recovery throughout the asset class. However, this price recovery was limited to popular cryptocurrencies. Many of the smaller altcoins that saw trading during the height of the bull market remain worthless and untraded. Per Figure 2, liquidity has also recovered. However, as shown in Figure 3, a great deal of this resurgence in total market transaction volume as of today can be attributed to Tether, which was relatively inactive during the bull market of 2017-2018.

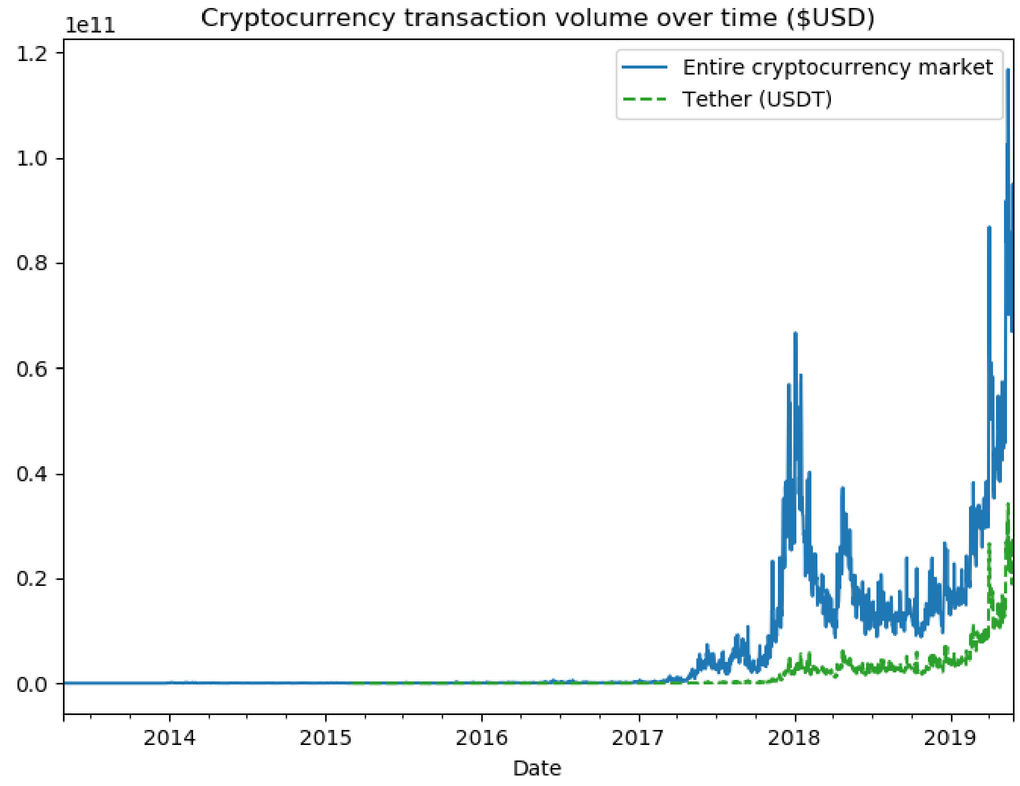

Figure 2 – *Daily transaction volume in USD for all coins in the dataset vs Tether*

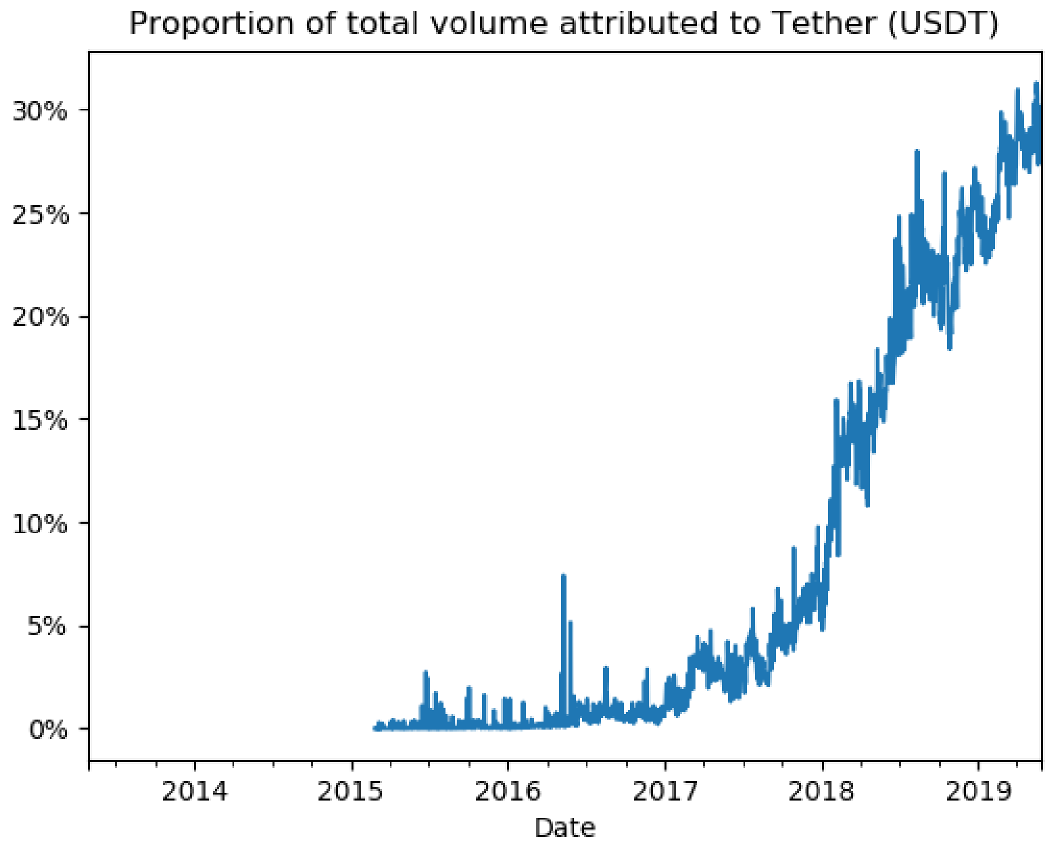

Figure 3 – *Percentage of total cryptocurrency daily transaction volume in USD associated with Tether*

Statistical Arbitrage

We offer a quick definition of statistical arbitrage. The term 'Statistical Arbitrage' can be used to describe a myriad of different investment strategies. However, these investment strategies generally have a certain set of features in common. These features are:

(i) Rules-based trading signals
(ii) A statistical mechanism for generating excess returns

Many of these investment strategies follow a 'pairs-trading' strategy. That is they are based on the concept of relative pricing. A pair of securities with similar characteristics must be priced more or less the same. We can model this relationship between time t=0 and t=t for a stock A and a stock B mathematically:

$$\ln\left(\frac{A_t}{A_{t_0}}\right) = \alpha(t - t_0) + \beta \ln\left(\frac{B_t}{B_0}\right) + X_t \tag{1}$$

The spread, X_t can be thought of as the degree of mutual mispricing. Strategies generally model this spread as a mean-reverting, stationary process. In this way, deviations from the equilibrium present trading opportunities. The strategy operates under the fundamental assumption that this mispricing will correct itself (Vidyamurthy, 2004). It is also possible for scenarios where a security may simply outperform its associated pair for a given period. This basis for the strategy proposed in this paper is mean reversion, so we ignore such scenarios.

As opposed to relative pricing between pairs of securities, in this paper we study the pricing of cryptocurrencies relative to a set of factors. We generate these factors via principle components analysis. The generation of these factors will be discussed in more detail later. Mathematically speaking, the returns of a cryptocurrency can be decomposed into an idiosyncratic and a systematic component, where the systematic component is spanned by the β of the coin relative to the factors:

$$\frac{\mathrm{dP_t}}{P_t} = \alpha dt + \sum_{j=i}^{n} \beta_j F_t^j + dX_t, \tag{2}$$

where α represents the 'drift' of the idiosyncratic component and $dX_i(t)$ is the increment of a stationary stochastic process which models price fluctuations in the price not reflected by the factor. In practice, given the average expected reversion time of cryptocurrencies and the magnitude of α, the drift term is insignificant.[7] The validity of the model across individual cryptocurrencies can easily be statistically tested.[8]

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[7] See Avellaneda and Lee for further justification
[8] See the appendix for a sample regression output

Literature review

The literature regarding pair-trading and statistical arbitrage in traditional financial markets is rich and continues to develop as researchers incorporate new and more complex numerical techniques into strategies. Elliott, Van der Hoek and Malcolm (2005) produce an analytical framework using a mean-reverting Gaussian Markov chain model for the spread. Gatev, Goetzmann and Rouwenhorst (2006) a year later introduce the seminal paper into the performance of a pairs-based trading strategy. They employ a simple algorithm where a pair for a given stock is formed through finding the security which minimises the sum of squared deviations between the two normalised price series. Using such an algorithm, they generate annualised excess returns of up to 11%.

These pairs-based strategies are all generally ‘contrarian’. They signal to place orders against the market trend. Early work on such mean-reversion uncovered evidence that supports such strategies, that financial markets do exhibit trend-following behaviour and price overreaction, and that trends tend to be followed by subsequent reversals (Lehmann, 1990). Avellaneda and Lee (2010) model US equity returns relative to the returns of both sector ETFs (existing and synthetic) and ‘eigen portfolios’ and develop a system to generate dimensionless trading signals based of the residuals of the aforementioned return equations. We use Avellaneda and Lee’s work as the basis of much of the strategy proposed.

However, the cryptocurrency literature is only in its infancy. Moreover, much of the literature focuses on both the volatility and viability of the asset class (Cermak, 2017; Hayes, 2016; Bianchi, 2018). Nonetheless, work has been done into the viability of model-based trading in cryptocurrency. Linthilhac and Tourin (2016), develop a dynamic pairs trading strategy for a portfolio of cointegrated cryptocurrencies. They back test their algorithm on a sample window from the 2014/07/01 to 2016/01/01 and find significant success. They observe that limited liquidity and market depth throughout their sample period could cause problems for practical implementation of the strategy and may distort a theoretically profitable trade into a losing one.

Strategies using trading signals constructed by the Engle-Granger two-step approach have also been tested by the literature. Van den Broek (2018) and Leung & Hung, (2018) independently use the cointegration approach to develop cryptocurrency pairs and cointegrated portfolios respectively. Van den Broek finds trading profitability between a number of valid pairs and Leung and Hung reach a similar conclusion. The principal finding is that despite practical limitations to the execution of some of the trades they outline in their research, the efficient market hypothesis does not hold for cryptocurrency markets and there is certainly room for statistical arbitrageurs to earn an abnormal profit.

Data

The data is retrieved from cryptocompare.com, a website that provides both real time data and historical cryptocurrency trading data from over 70 exchanges, using their free API, and then cross-checked against historical data retrieved from web scraping coinmarketcap. Cryptocompare supports 3873 cryptocurrencies on their platform. We exclude all coins not traded in the last 24 hours. This leaves 1036 coins in the dataset. We then retrieve historical OHLCV (Open, High, Low, Close, Volume) daily transaction data for each of these 1036 currencies in USD to 28/05/2019. The closing price is the price at 12AM midnight on that day. The price on Cryptocompare is derived from the CCCAGG[9], the Crypto Coin Comparison Aggregated Index; a real time index built to provide the best price estimation, across exchanges and using a 24-hour volume weighted average.

Coinmarketcap's price is a volume weighted average of market pair prices for the cryptocurrency.[10] Not all cryptocurrencies may have a USD market pair, but major coins such as Bitcoin and Ethereum do. For instance, consider a lesser-known cryptocurrency such as AION. AION may have no direct USD pair but have AION/ETH and AION/BTC pairs. ETH and BTC have USD reference prices and so AION/USD is computed as a volume weighted average of these market pair prices.

The cryptocurrencies included in the dataset are spread among the various subclasses. Stablecoins, tokens and coins are all included. Given the relative infancy of blockchain technology, and the continuous arrival of new coins to the market, there is then a huge inconsistency in the first trade date between the coins in the dataset.

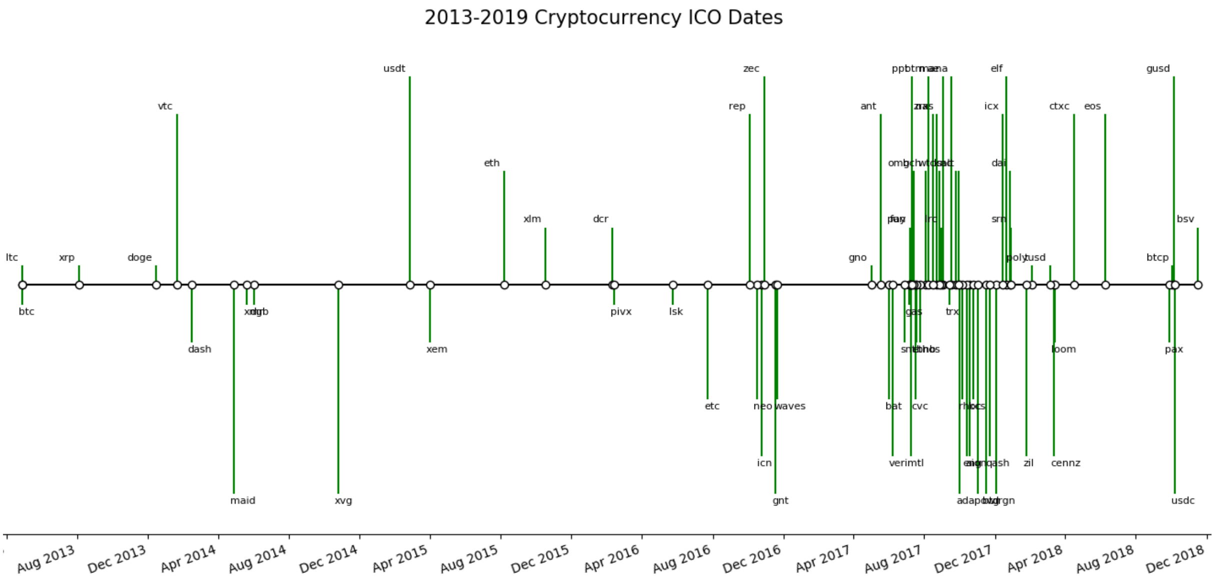

Figure 4 – Timeline of first trade dates for a sample of coins in the dataset

9 https://www.cryptocompare.com/media/27010937/cccagg_methodology_2018-02-26.pdf
10 https://coinmarketcap.com/methodology/

Figure 4 makes the staggered entrances of cryptocurrencies to the market apparent. Many cryptocurrencies in the dataset have been floated only relatively recently, the bulk of which in 2017 and 2018, at the height of the cryptocurrency bubble. Figure 5 below demonstrates this clearly.

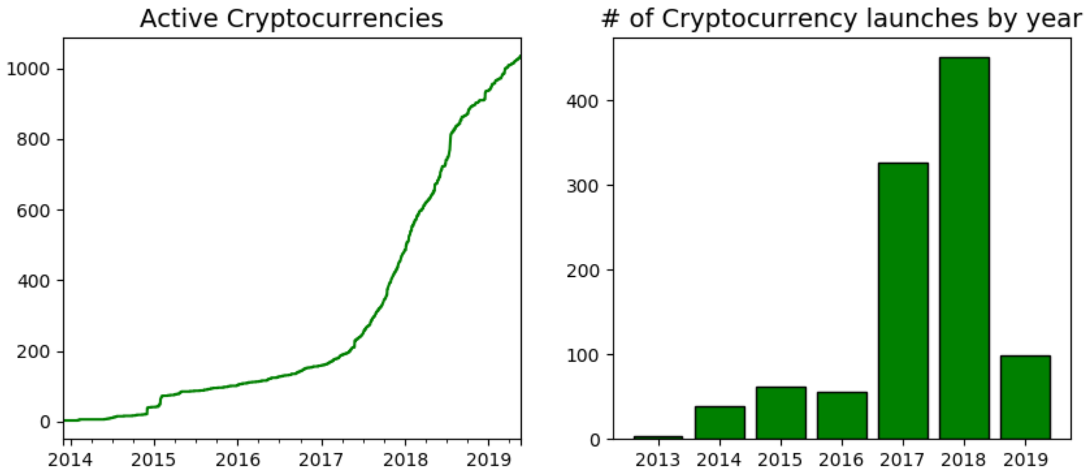

Figure 5 – Active Cryptocurrencies and Number of Coins launched by year

The infancy of the cryptocurrencies as an asset class in presents a challenge in selection of a suitable sample period. Choosing a sample window beginning to far back in time will greatly limit the number of distinct cryptocurrencies in the sample. However, choosing a sample window that ends too close to today will leave us unable to test the algorithm out-of-sample. Luckily, unlike equities, cryptocurrencies can be traded 24/7. Cryptocurrency exchanges are digitalised and operate around the clock and hence the trading year for cryptocurrencies is a full 365 days.

Table 1 – Characteristics of sample data

Summary (days actively traded)			
Mean	574.612	**25%**	311
Standard Deviation	412.316	**50%**	490
Min	2	**75%**	683.75
Max	2001		

Table 1 clarifies the issue. 50% of coins in the dataset only begun trading 490 days ago. Thus we select 2018/1/1 – 2019/1/1 as our sample period. 429 coins were traded at this time. This leaves 2019/1/1 – 2019/5/28 to test the algorithm out of sample. However, as the strategy involves regressing returns on a trailing window of factor returns, only cryptocurrencies that are active prior to the beginning of this window are eligible for inclusion. The size of the sample is thus dependent on the size of this window. Given the influx of cryptocurrency floats towards the end of 2017 many of these 429 coins will then be removed from the sample. The sample contains the five major coins BTC, LTC, DASH, XRP and ETH, more prominent altcoins like DOGE and a handful of Stablecoins such as Tether. Hence this sample captures an accurate snapshot of the cryptocurrency universe.

Methodology

A number of python packages are utilised in order to efficiently perform the statistical analysis described here. Namely sklearn, pandas, numpy, statsmodels and matplotlib.

Principle component analysis has long been known as a technique to reduce the dimensionality of a dataset and has widespread applications. Within the world of finance, PCA has been used to model the yield curve, hedge fixed income portfolios and more. Principle components analysis can be used to identify latent, 'hidden' factors in a dataset, by producing principle components that are linear combinations of the observed variables. In this sense, principle components analysis allows a dataset to 'speak for itself'. Each principle component seeks to explain the maximal amount of variance remaining in the system, whilst being orthogonal to the other principal components. Naturally then, the first principle component explains the biggest proportion of the variance. Application of principle components analysis in US Equities by Kim and Jeong (2005) decomposed the variance of the dataset into three parts:

1. The first principal component, which represented market-wide effects that influence all stocks
2. Some number of subsequent principle components, which may capture fluctuations in specific groups or sectors of stocks
3. The remainder of the principle components; attributed to noise

Yang & Rea (2017) delved further into the high-numbered principle components which Kim and Jeong attributed to the 3rd category in an analysis of Australian equities. They found the last few principle components could be used to identify highly correlated pairs or larger groups of stocks. Whilst intuitive interpretation of principle components is difficult, these studies shed much light.

We position ourselves at the beginning of the sample, i.e. on the 2018/1/1. We transform daily price data for the cryptocurrencies for a trailing window into returns through taking the difference in log prices. Then we create a m x n matrix of daily returns, where m is the length of the trailing window and n is the number of coins in the sample. From here, we take the standardised returns for each coin i by subtracting the mean of the i-th's coins return and dividing by the standard deviation of its returns. Mathematically the standardised daily return of each coin i at time k is:

$$\widehat{R_{ik}} = \frac{R_{ik} - \overline{R_i}}{\sigma_i}, \tag{3}$$

where $\overline{R_i}$ is the average return for the i-th coin over the trailing window and σ_i is it's standard deviation. We then apply PCA to the covariance matrix of this series of returns; equivalent to applying PCA to the correlation matrix.

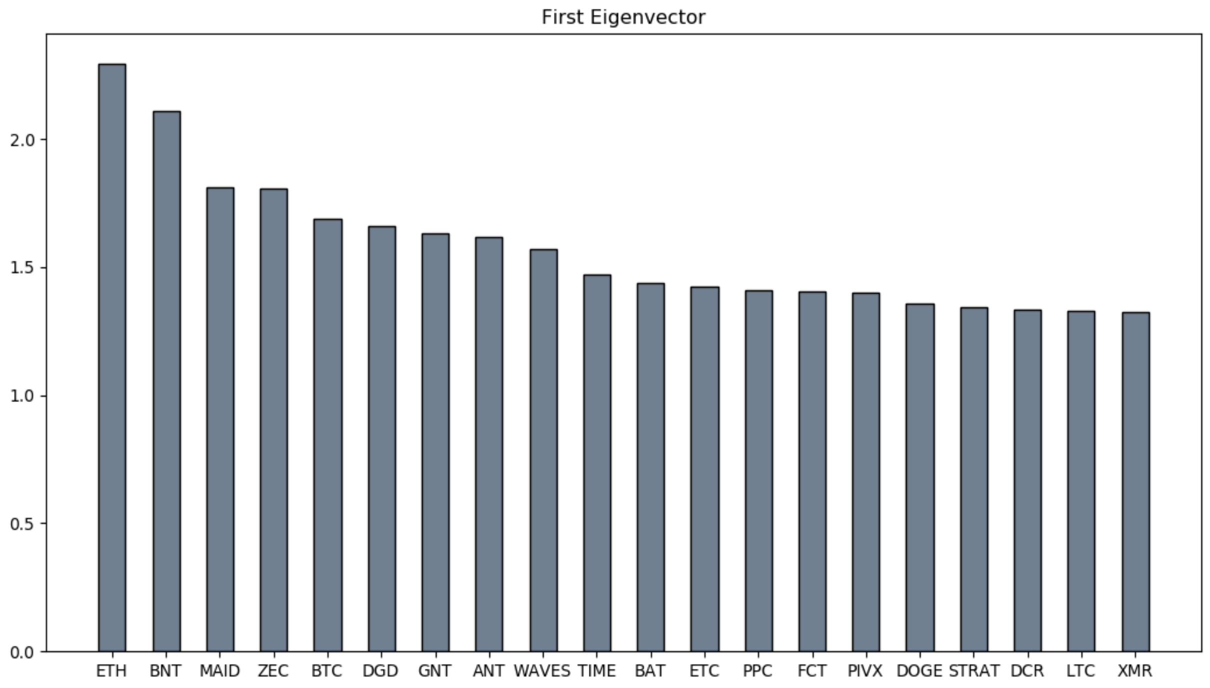

Figure 6 – First 20 coefficients of the first eigenvector sorted by size estimated on the 2018/1/1 using a trailing window of 180 days

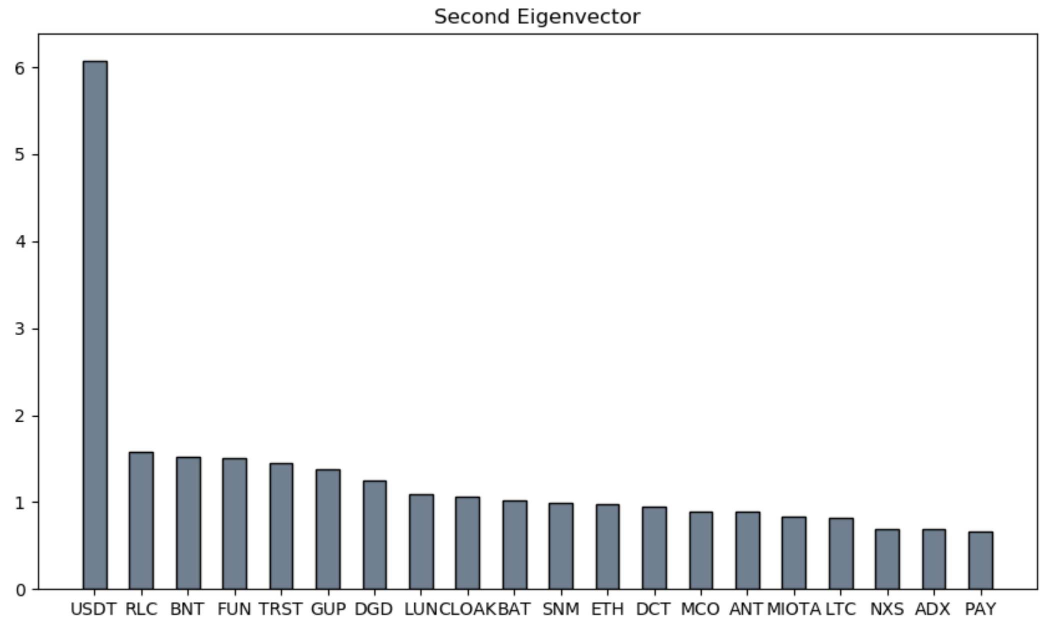

Figure 7 – First 20 coefficients of the second eigenvector sorted by size on the 2018/1/1 using a trailing window of 180 days

Figure 6 and Figure 7 present a visualisation of the top 20 coefficients associated with the first and second principal components or eigenvectors, ranked by size, computed on the first day of the sample using a 180-day window of trailing historical returns. The coefficients of the eigenvectors display some interesting results. We see that cryptocurrencies based on prominent blockchains such as Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP) all rank in the top 20 coefficients on the first eigenvector. The majority of the other currencies with high loadings on the first principle component are tokens launched as a capital raising by a crypto-related venture mentioned in the introduction. Examples include Bancor (BNT), which offers a marketplace with automated market makers to exchange crypto assets that are illiquid on exchanges, MaidSafeCoin (MAID), the currency for the SAFE Network, an autonomous and decentralized data network that facilitates the sharing of digital resources such as processing power and DigixDAO (DGD) a project to build infrastructure that specializes in the tokenization of physical assets.

Interestingly, Tether has a large loading in the second eigenvector, and this much lends credence to Griffin and Shams (2018) findings that Tether is used as a tool for price manipulation. Of the coins with the 20 highest loadings in the second eigenvector, we find that 15 of these are ERC20 tokens based on the Ethereum blockchain. The second eigenvector is seemingly capturing an ‘ERC20’ token ‘subclass’ effect, much like the 2nd category espoused by Kim and Jeong (2005).

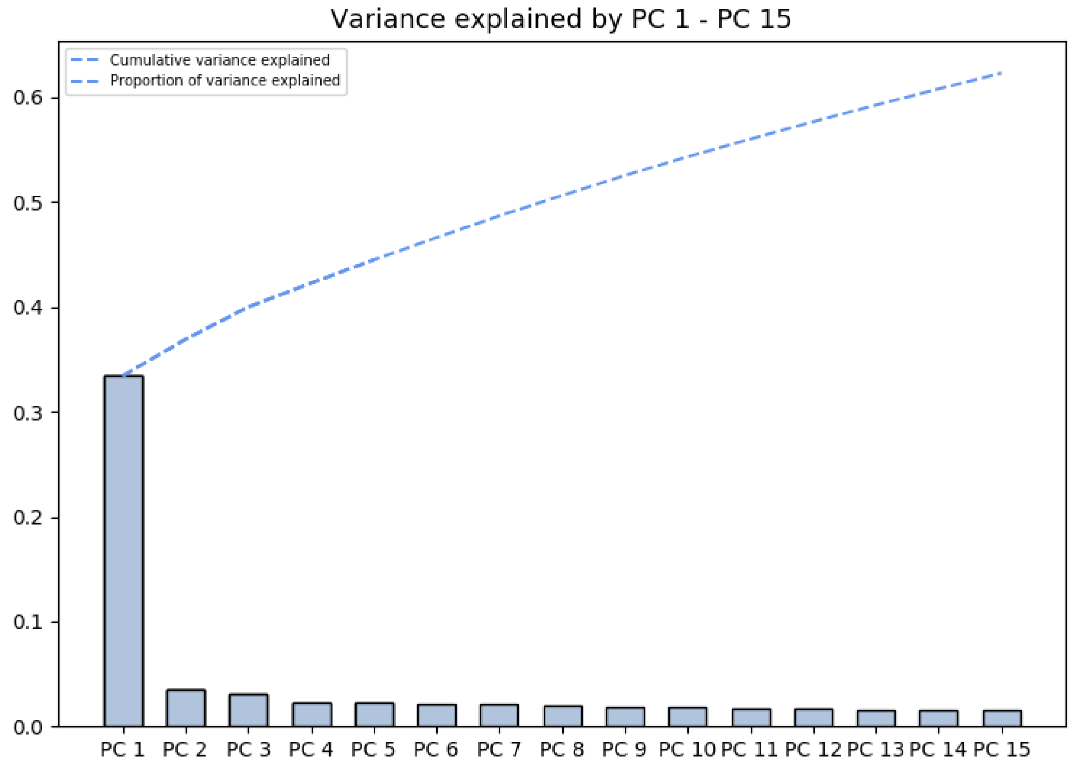

Figure 8 – The variance explained by the first 15 principle components estimated on the 2018/1/1 using a trailing window of 180 days

As per Figure 8, the first principal component explains majority of the total variance, 33.43% in this case. Cumulatively, the first 15 principal components explain 62.3% of the total variance.

From these eigenvectors, we are able to compute 'eigen portfolios' that correspond to each eigenvector. We follow the methodology outlined in Avellaneda and Lee (2010) to build these eigen portfolios for an arbitrary number of eigenvectors. The construction is as follows.

Let $v_i^{(j)}$ and σ_i denote the coefficient of the i-th coin in the j-th eigenvector and the standard deviation of the i-th coin's returns in the last x days respectively, where x is the length of the trailing PCA window. The weight of the i-th coin in the j-th eigenportfolio is then defined as:

$$Q_i^{(j)} = \frac{v_i^{(j)}}{\sigma_i}$$

From here, computation of the portfolio return is trivial. The return of the j-th eigenportfolio is:

$$F_j = \sum_{i=1}^{N} \frac{v_i^{(j)}}{\sigma_i} R_i \tag{4}$$

These weights are inversely proportional to a coins volatility – consistent with capitalisation-weighting, as coins with greater market capitalisations exhibit lower volatility.

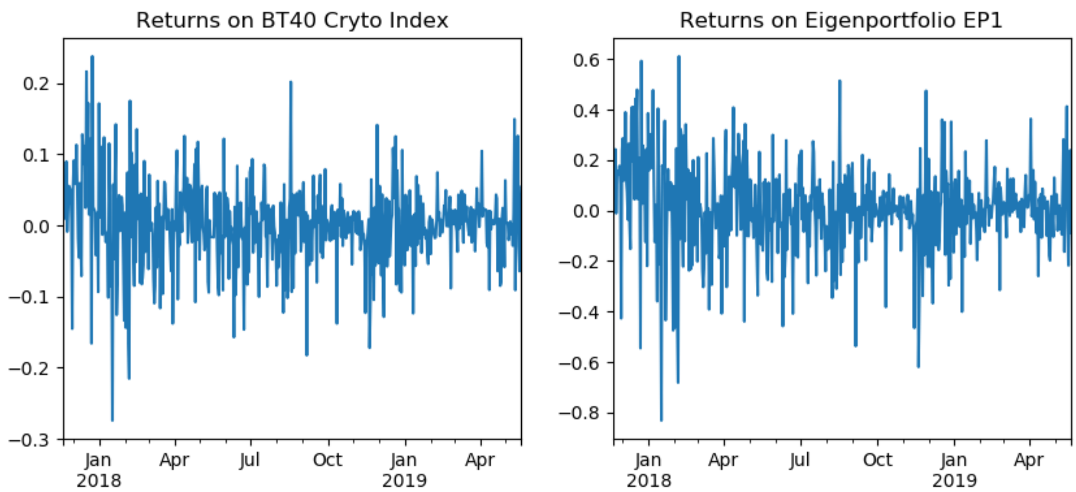

Figure 9 – Evolution of daily returns of the Bletchley 40 Index and the first eigen portfolio

Figure 9 presents subplots of the daily returns experienced by the first eigenportfolio and the daily returns of the Bletchley 40 index. The Bletchley 40 Index is a market-cap weighted index composed of 40 small size digital assets by market capitalisation.[11] Further comparisons against other Bletchley Indexes are in the appendix. The first eigenportfolio is clearly a relatively good proxy for the movement of the Bletchley Index. Assuming the Bletchley Index provides an accurate reflection of market-wide movements, clearly the first eigenportfolio reflects market effects.

[11] https://www.bletchleyindexes.com/methodology

With the historical returns of the eigen portfolios calculated, we can now model the returns of each coin according to equation (2). We select some arbitrary regression window y and regress the returns of each coin for the last y days on the returns of an arbitrary number of eigen portfolios, z in for that same window. Empirically, we find a regression window of length 50 days and the first 5 eigen portfolios to be appropriate. Avellaneda and Lee (2010) use a regression window of 60 days to capture a full earnings cycle for equities but evidently no such economic rationale exists for cryptocurrencies. The regression for the i-th coin against the returns of the first 5 eigenportfolios takes the form:

$$R_i = \beta_0 + \sum_{j=1}^{5} \beta_j R_j + \epsilon_i \tag{5}$$

Returns also satisfy equation (2). The OU process is defined as the cumulative sum of the residuals

$$X_t = \sum_{i=1}^{t} \epsilon_i \quad t = 1,2, \dots ,50,$$

We then model the mean-reverting Ornstein-Uhlembeck process, which has the differential form:

$$dX_t = k(m - X_t)dt + \sigma dW_t, \tag{6}$$

With conditional mean m and variance $\frac{\sigma^2}{2k}$. This stochastic differential equation can be transformed into an AR(1) regression of form:

$$X_{t_0+\Delta t} = a + bX_{t_0} + \zeta$$

This AR(1) regression can easily be performed for the 50 day window. From the coefficients of the AR(1) regression a, b, and ζ, the parameters of the OU process can be estimated in the following way:

$$k = -\frac{\ln(b)}{\Delta t} \tag{7}$$

$$m = \frac{a}{1 - b} \tag{8}$$

$$\sigma = \sqrt{\frac{Variance(\zeta) \times 2k}{1 - b^2}} \tag{9}$$

The parameter k describes the mean reversion time of each coin. We are able to exclude coins that do not exhibit fast enough mean reversion times relative to the regression window. If b is too close to 1 then we can reject the model for the coin and exclude it from trading.

Trading Signals

We do the above process at the close of each trading day for each coin in the sample. Thus, we are able to construct trading signals for every day in the sample looking back at the historical record.

We define a dimensionless ‘s-score’, which is essentially a standardisation of the residual Xt process. The s-score measures the distance to equilibrium of the cointegrated residual in units standard deviations, i.e. how far away a given stock is from the theoretical equilibrium value associated with our model. It is defined as:

$$s = \frac{X_t - m}{\sigma / \sqrt{2k}} \tag{10}$$

As a result of the betas and the residuals being estimated with the same sample,

$$X_{50} = 0$$

Hence we have:

$$s_i = \frac{-m_i}{\sigma_i / \sqrt{2k_i}} \tag{11}$$

We also introduce a modification made by Avellaneda and Lee (2010) to help remove model bias. They propose that since in aggregate stocks are correctly priced, using an adjusted mean for computation of scores, where

$$\overline{m_i} = m_i - \frac{1}{N}\sum_{j=i}^{N} m_j,\ i = 1,2,\dots,N,$$

and we simply subtract the average ‘m’ calculated across the coins in the sample.

We then use these s-scores to develop trading signals. We set some thresholds for the s-score that signal whether to open or close a long or short position in a given coin. There are then 4 such thresholds

Open long position if $s_i < -\bar{s}_{open\ long}$

Open short position if $s_i > +\bar{s}_{open\ short}$

Exit long position if $s_i > -\bar{s}_{close\ long}$

Exit short position if $s_i < +\bar{s}_{close\ short}$

Figure 10 illustrates how this works graphically, with $\bar{s}_{open\ long} = 1.25$, $\bar{s}_{open\ short} = 1.25$, $\bar{s}_{close\ long} = 0.5$ and $\bar{s}_{close\ short} = 0.75$ using Litecoin as an example. Given s is a dimensionless variable, these thresholds are constant across coins in the sample. The rationale is to entre trades when the s-score is far enough from equilibrium and to close them as they near zero.

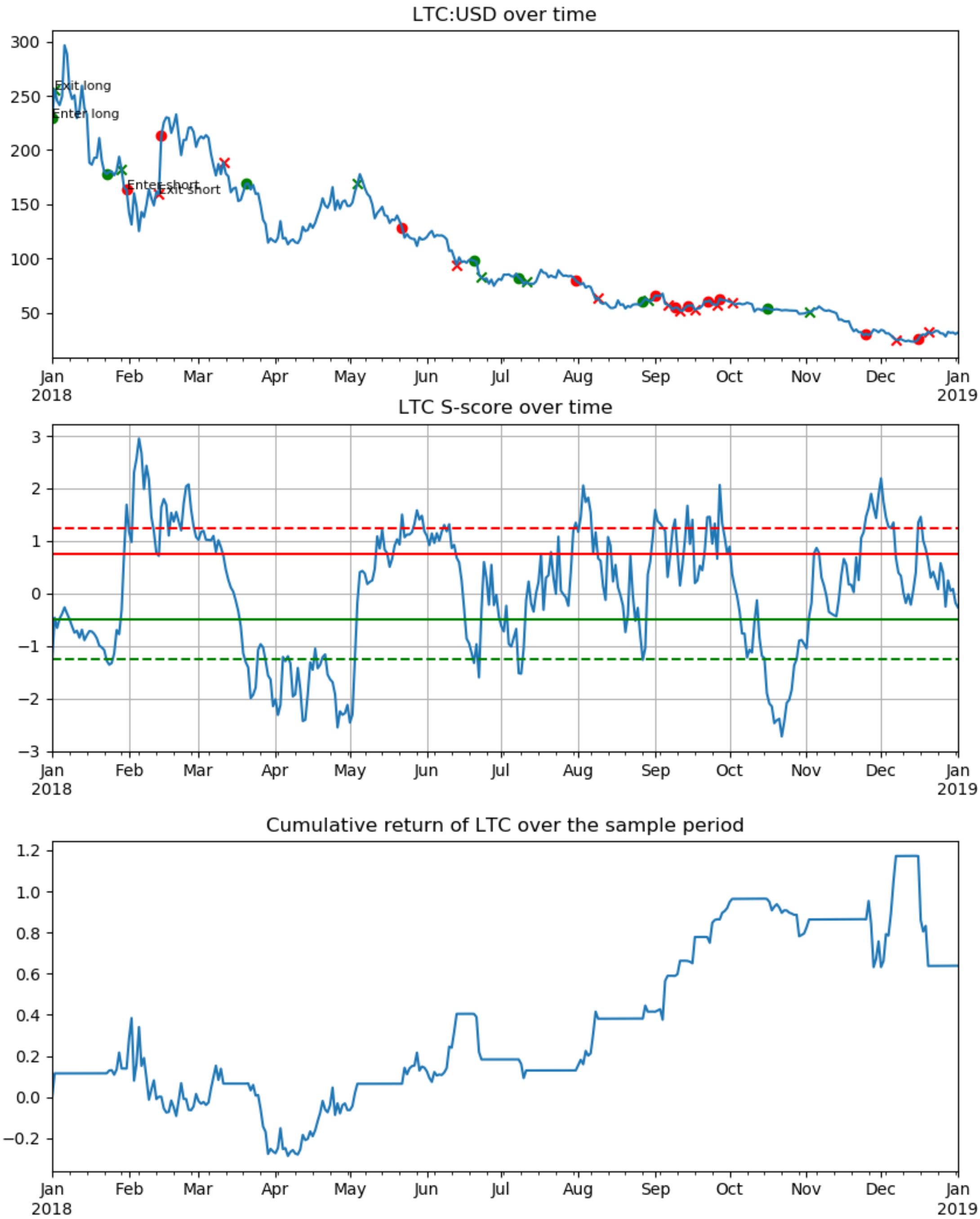

Figure 10 – Subplots depicting the evolution of the s-score for LTC over the sample, an annotated LTC:USD price chart with the entry and exit dates of the first long and short positions and the cumulative return on LTC by making such trades. Green (red) circles depict entering a long (short) position and green (red) crosses denote exiting that long (short) position. Dotted green (red) lines represent the threshold for opening long (short) positions and solid green (red) lines represent the threshold for exiting long (short) positions.

When the model detects no trade to be made, the capital allocated to that coin is instead invested in bonds, assumed to have an annual return of 1.5%, hence the flat periods in the third subplot. When a signal is detected, the full amount is invested in the appropriate position.

Profit and Loss

Signals are computed at the end of each closing day, and trades are executed at the beginning of the next day - the return is the difference between the close-to-close prices. This can be hard to visualise given the 24/7 nature of cryptocurrency exchanges. Consider the 'close of the trading day', i.e. 12 AM midnight on 2018/5/1. We then compute signals for the next trading day and execute those trades 'when the market next opens', i.e. 12:01 AM of the next day 2018/5/2. Hence, on 2018/5/1 we receive the return for all the positions held from the start of that day, and on 2018/5/2 we receive the return for all the positions open as of the close of 2018/5/1.

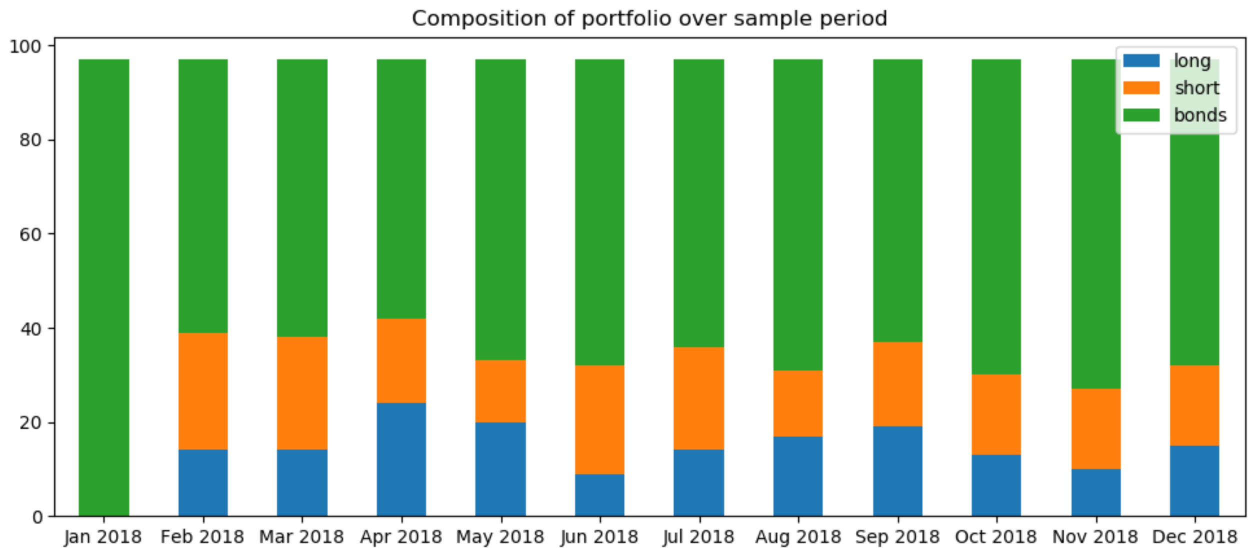

Figure 11 – An illustration of the portfolio composition throughout the sample period. Orange denotes open short positions, blue denotes open long positions and green represents the proportion in bonds.

First note that at the start of the sample period an equal amount of the initial capital is allocated to each coin. The cumulative return on trades made in each cryptocurrency will determine the size of the final holding of the portfolio in that cryptocurrency at the end of the period.

Let the daily return of the i-th stock be R_i. The return on a long position in the i-th stock is:

$$R_{long} = R_i.$$

The daily return on a short position in the i-th stock is:

$$R_{short} = -R_i.$$

The model may not detect any trades. Hence the capital will be invested in bonds for this period. The annual return on bonds is assumed to be 1.5%. The daily return on a position in bonds is:

$$R_{bonds} = {}^{1.5\%}/_{365} = 0.0000411$$

We then have the daily returns series for each asset in our portfolio. Hence, provided an initial dollar amount in that asset, we can easily plot how this asset and hence the portfolio in aggregate evolves in value over time. Slippage is incorporated by deducting 20 bp. from the daily return for each trade made.

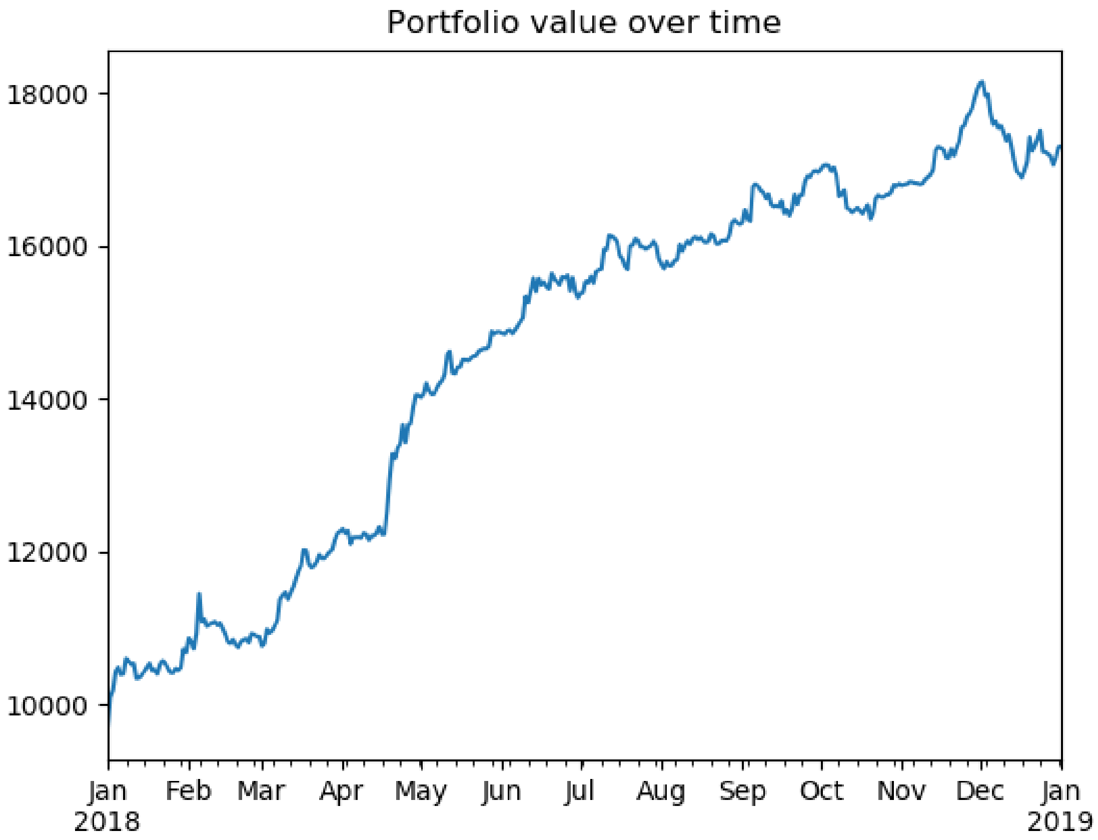

Figure 12 – A graphical depiction of the evolution of the portfolio value throughout the sample period. This portfolio corresponds to trading using a PCA window of 160 days, a regression window of 50 days, 5 principle components and an initial allocation of 100$ to each of the 97 coins in the sample.

Sharpe Ratio

The Sharpe Ratio is defined as:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p}$$

Where the parameters are the annualized return of the portfolio, the annual risk-free rate and the standard deviation of the portfolio's excess return. The above portfolio has a standard deviation of returns of 15.63% and an annual return of 78.47%. The Sharpe ratio of the portfolio is then 4.924. Despite the volatility of the cryptocurrency asset class being some of the highest amongst investment options, the consistently large position in bonds (>50% of the portfolio at all times as per Figure 11) helps offset some of this.

Back testing

The algorithm can be broken down into two components. The first component relates to computation of the s-scores, which is affected by the inputs below. The second component relates to the interpretation of these s-scores into appropriate trading signals.

Computing the s-scores

Let *A* denote the length of the fixed rolling window to conduct PCA to find our eigen portfolios. Let *B* denote the length of the fixed rolling window to use for the regression. Let *X* denote the frequency with which we recompute the weights of the eigen portfolios, where X is the interval between re-computation in days. Let *Y* denote the number of principal components and lastly let *Z* denote the volume threshold during the sample period for trading eligibility.

Back testing of the algorithm is done for the sample period (2018/1/1 -2019/1/1). We filter out coins that have not traded for length A days prior the first day in the sample (2018/1/1). We then filter out all coins that do not meet the liquidity threshold. We back test the algorithm using a number of different combinations of these input variables and compute the performance of each. The results of back testing with respect to A, B and Y are reported in Tables 3-5 below. Results from changing other input variables are featured in the appendix. For the back tests here, we use the same signal cut-offs as in Figure 10. Avellaneda and Lee (2010) suggest a PCA window of 252 days, 15 PCA factors and a regression window of 60 days to capture a full earnings cycle for US equities. Clearly; assigning these parameters is not so straightforward for cryptocurrencies.

Table 2 – Trading results from varying the number of principal components

Changing number of PCS

Annual Return	PCA Window	Regression Window	# of PCs	# of Profitable Coins
37%	180	50	6	45
36%	180	50	5	42
34%	180	50	2	44
30%	180	50	1	43
28%	180	50	8	42
28%	180	50	9	39
28%	180	50	7	35
26%	180	50	4	38
24%	180	50	3	40
15%	180	50	15	32
10%	180	50	13	37
9%	180	50	10	35
9%	180	50	11	36
8%	180	50	14	32
8%	180	50	12	36

Table 3– Trading results from varying the length of the rolling regression window

Changing length of the rolling regression window

Annual Return	PCA Window	Regression Window	# of PCS	# of Profitable Coins
43%	180	30	5	49
36%	180	50	5	42
36%	180	35	5	44
33%	180	100	5	41
28%	180	105	5	37
26%	180	90	5	42
21%	180	45	5	40
20%	180	70	5	40
20%	180	95	5	37
19%	180	55	5	37
14%	180	80	5	29
13%	180	60	5	35
12%	180	75	5	33
10%	180	65	5	37
8%	180	85	5	35
6%	180	40	5	28

Table 4 – Trading results from varying the length of the rolling PCA window

Changing the length of the PCA rolling window

Annual Return	PCA Window	Regression Window	# of PCS	# of Profitable Coins
63%	160	50	5	52
59%	150	50	5	52
47%	130	50	5	59
46%	110	50	5	54
46%	170	50	5	46
38%	140	50	5	48
37%	120	50	5	61
34%	100	50	5	59
36%	180	50	5	42

The first column is the annual return, the second the length of the trailing window used for PCA, the third the length of the trailing window used for the regressions, the fourth the number of eigen portfolios in the returns regression and the fifth the number of coins that ended up with a positive cumulative return, out of a possible 97. We want to avoid over-fitting, but for an asset class like cryptocurrency coming up with an economic rationale for assignment of the model parameters is difficult – there is no seasonality, or earnings cycles. Back testing is done in the interest of gleaning some understanding of what values for each of the variables allow the model to best capture the market dynamics.

Finding optimal signal cut-offs

We consider performance using signal thresholds where we enter long (short) and exit long (short) positions earlier and later. Using the s-scores computed with a PCA window of 160 days, a regression window of 50 days and 5 principle components. We adjust the cut-offs $\bar{s}_{open\ long}$, $\bar{s}_{open\ short}$, $\bar{s}_{close\ long}$ and $\bar{s}_{close\ short}$, and report the results below.

Table 5 – Trading results from varying $\bar{s}_{open\ long}$

$\bar{s}_{open\ long}$	Annual Return	σ	Maximum Drawdown	Sharpe Ratio
-1	61.18%	15.78%	-355.50	3.78
-1.05	67.25%	15.54%	-350.20	4.23
-1.1	69.61%	15.15%	-330.26	4.49
-1.15	74.21%	15.56%	-362.84	4.67
-1.2	74.15%	15.40%	-337.44	4.72
-1.25	78.48%	15.63%	-371.58	4.93
-1.3	77.28%	15.64%	-395.99	4.85
-1.35	80.48%	16.43%	-413.97	4.81
-1.4	84.97%	16.58%	-447.79	5.03
-1.45	83.35%	16.16%	-446.01	5.07
-1.5	82.63%	16.27%	-446.01	4.99

Table 5 – Trading results from varying $\bar{s}_{open\ short}$

$\bar{s}_{open\ short}$	Annual Return	σ	Maximum Drawdown	Sharpe Ratio
1	96.49%	18.67%	-470.392	5.088
1.05	96.11%	17.87%	-465.174	5.294
1.1	88.53%	17.29%	-462.088	5.035
1.15	84.35%	16.78%	-448.704	4.937
1.2	82.58%	16.54%	-447.488	4.901
1.25	84.97%	16.58%	-447.795	5.033
1.3	80.02%	15.91%	-393.469	4.935
1.35	76.75%	15.59%	-360.591	4.825
1.4	75.53%	14.97%	-335.160	4.946
1.45	76.10%	14.55%	-330.259	5.128
1.5	67.42%	13.89%	-312.157	4.747

Again, the goal is not to over-fit parameters to the sample but to gain insight as to what optimal signal cut-offs could be for cryptocurrency markets, and understand how they may differ from Avellaneda and Lee (2010)'s cut-offs for US equities (which we use in Figure 11). Implementation of the model for live trading cannot blindly follow the cut-offs we find to maximise profit in-sample.

Table 6 – Trading results from varying $\bar{s}_{close\ long}$

$\bar{s}_{close\ long}$	Annual Return	σ	Maximum Drawdown	Sharpe Ratio
-0.2	78.56%	16.62%	-452.30	4.64
-0.25	82.00%	16.83%	-454.26	4.78
-0.3	84.35%	17.09%	-456.49	4.85
-0.35	88.84%	17.35%	-457.30	5.03
-0.4	91.22%	17.63%	-468.02	5.09
-0.45	92.25%	17.84%	-462.29	5.09
-0.5	96.11%	17.87%	-465.17	5.29
-0.55	89.57%	17.67%	-468.43	4.98
-0.6	90.37%	17.69%	-471.53	5.02
-0.65	89.38%	17.56%	-474.26	5.00
-0.7	90.73%	17.90%	-502.62	4.98
-0.75	89.52%	18.10%	-505.32	4.86

Table 7 – Trading results from varying $\bar{s}_{close\ short}$

$\bar{s}_{close\ short}$	Annual Return	σ	Maximum Drawdown	Sharpe Ratio
0.2	122.98%	27.70%	-779.85	4.39
0.25	118.11%	26.09%	-679.84	4.47
0.3	110.19%	25.41%	-653.86	4.28
0.35	106.75%	24.71%	-602.91	4.26
0.4	101.75%	23.46%	-584.69	4.27
0.45	95.18%	22.87%	-580.17	4.10
0.5	87.48%	22.50%	-580.16	3.82
0.55	95.74%	20.75%	-587.87	4.54
0.6	97.06%	19.86%	-553.91	4.81
0.65	98.30%	19.32%	-535.08	5.01
0.7	95.92%	18.80%	-538.92	5.02
0.75	96.11%	17.87%	-465.17	5.29

Unsurprisingly, exiting short positions later is substantially riskier but generates substantially higher returns. We find that in-sample the best performance is observed opening entering long positions later and opening short positions earlier. This is summarised by following the trading rules:

Open long position if $s_i < -1.4$

Open short position if $s_i > +1.05$

Exit long position if $s_i > -0.5$

Exit short position if $s_i < +0.75$

These rules result in annual returns of 96.11%, and a Sharpe ratio of 5.29. See appendix for plot.

Out-of-Sample performance

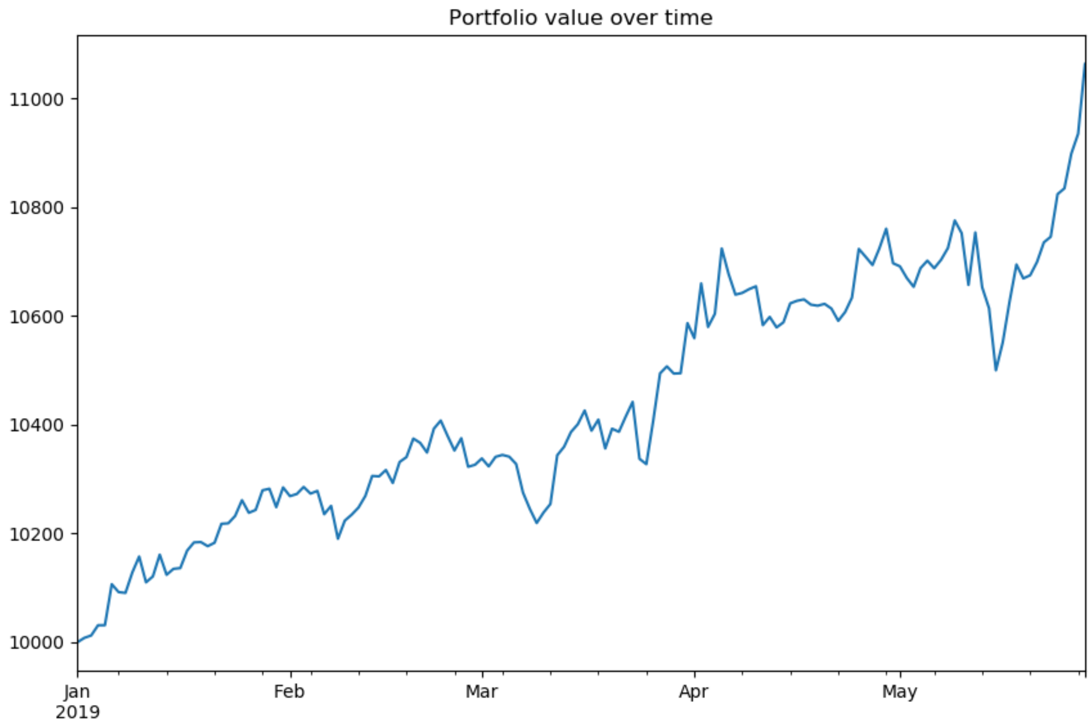

Figure 13 – Evolution of the value of a portfolio with $10000 USD in initial capital out-of-sample (2019/1/1 – 2019/5/28). This portfolio corresponds to trading using a PCA window of 160 days, a regression window of 50 days and the top 5 eigen portfolios.

The strategy performs admirably out of sample. To ward off data-snooping and avoid over-fitting, we use the same signal-cut-offs as in Figure 11, $\bar{s}_{open\ long} = 1.25$, $\bar{s}_{open\ short} = 1.25$, $\bar{s}_{close\ long} = 0.5$ and $\bar{s}_{close\ short} = 0.75$ as opposed to the profit-maximising thresholds observed in the Backtesting section. Effectively, we enter positions when the model suggests the relationship between the coin and the factors is 1.25 standard deviations away from the equilibrium and exit long (short) positions when it is 0.5 (0.75) standard deviations away. Out of curiosity, we fit the model out-of-sample with the profit-maximising cut-offs in the previous section and observe that it is indeed a case of

We can see some drawdowns, most notably recently midway through May. Over the course of the 147 days in the out-of-sample period, the portfolio returns 10.65%, and has an annual standard deviation of returns of 12.1%. This corresponds to an annual return of 28.57% and a Sharpe ratio of 2.26.

As the out-of-sample performance is not as impressive as in-sample, it may suggest such a systemic arbitrage approach is starting to be adapted by investors. Nonetheless, the positive return and Sharpe ratio shows that there remains substantial opportunity for implementation of the proposed strategy.

Volume and slippage concerns

Trading volume in cryptocurrency markets is relatively small compared to financial markets. Furthermore, trading volume throughout the asset class has suffered since the cryptocurrency bubble burst at the beginning of 2018. This effect is more pronounced in lesser-known altcoins. This raises practical concerns for any trading strategy involving cryptocurrencies.

Only coins with trading volume above $10000 for every day through the entire sample period (2018/1/1 – 2019/1/1) were included in the sample. Trading volume is negatively correlated with slippage. Figure 5 demonstrates that as daily transaction volume increases slippage decreases.[12]

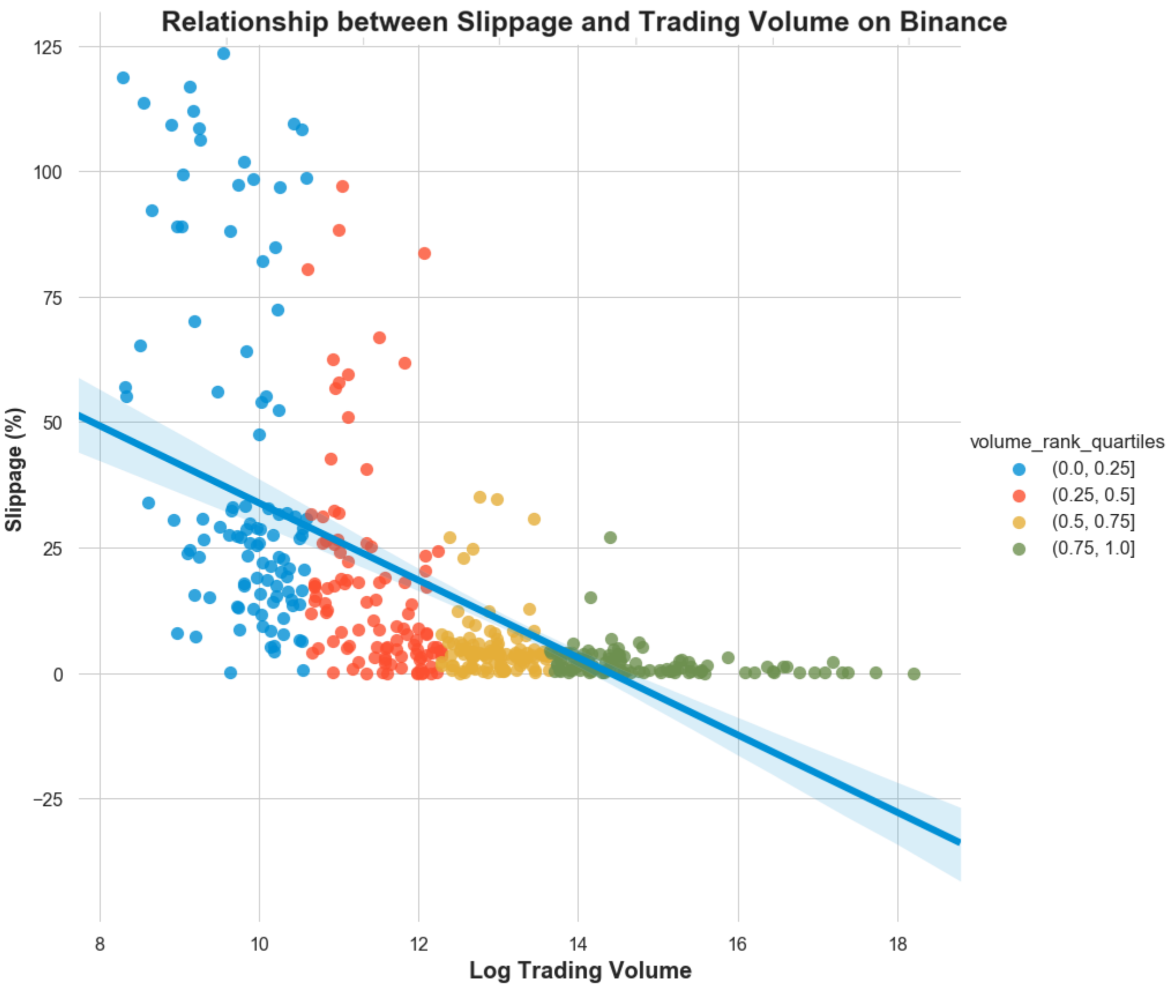

Figure 14 – Slippage faced on execution of a $5000 order across different pairs by trading volume

Source: https://www.hodlbot.io/blog/an-analysis-of-slippage-on-the-binance-exchange

Figure 14 displays the slippage faced upon execution of an order of $5000 USD across a number of cryptocurrency pairs on the Binance cryptocurrency exchange. It can be seen that an order across a pair with low trading volume may face slippage of up to 120%. Evidently, there is not nearly enough

12 https://www.hodlbot.io/blog/an-analysis-of-slippage-on-the-binance-exchange

depth in the order book for orders of such size in the markets for these low volume pairs. Certainly, these levels of slippage in almost >50% of currencies make the practical implementation of any trading strategy in them.

However, slippage is much closer to zero and much closer to that which we would see in typical financial markets for cryptocurrencies in the top quartile by trading volume. The benchmark in this case is a log trading volume of just under 13. Cryptocurrencies in which log daily trading volume surpasses this threshold of 13 face a much more normal slippage. Table 5 presents summary statistics for the average log daily transaction volume in USD across all coins in the sample.

Table 8 – Summary statistics of average log daily volume across coins in the sample

Summary – average daily log(volume)			
Mean	15.858658	**25%**	14.563885
Standard Deviation	2.102146	**50%**	15.420358
Min	12.615660	**75%**	16.772847
Max	22.524778		

The median log daily volume for coins in the sample is 15.42. As per Figure 5, an order to the magnitude of $5000 USD in cryptocurrency pairs with a daily log volume of 15.4 face slippage close to zero. In addition, the 25th quartile for mean log daily volume across coins in the sample is 14.56; transactions in cryptocurrency pairs with this level of liquidity also face only a small amount of slippage.

Hence, given that the size of the orders proposed by the strategy, and the above findings relating transaction volume to slippage, we can conclude that hypothetical trades determined by the strategy in our sample are unlikely to impact prices. Our assumption of a slippage cost of 0.2% or 20 basis points per trade is reasonable.

Nonetheless, it is evident that the scalability of such a strategy is limited. The order book is shallow across many cryptocurrencies, and large institutional scale orders will heavily influence price in all cryptocurrency pairs outside of the top 20 by volume. This may help explain the profitability of the strategy discussed in this paper. Cryptocurrency markets are unprepared to absorb the trades of large, institutional investors and hence the mean reversion mechanics underpinning the strategy will break down. Thus, they ignore the asset class entirely. Evidence to support this hypothesis comes from the Chicago Board Options Exchange recently announcing they will no longer offer Bitcoin futures, citing a lack of institutional interest.[13]

[13] https://www.wsj.com/articles/cboe-abandons-bitcoin-futures-11552914001

Conclusion

The proposed strategy is found to be highly profitable. By using principle components analysis we allow the data to speak for itself. In doing so, we are able to develop pricing factors and establish equilibrium relationships for the price of each cryptocurrency relative to these factors. Deviations from the equilibrium enable us to generate substantial trading profits. The strategy nets an exceptional in-sample Sharpe ratio of 9.4. The declining profitability of the strategy out-of-sample is certainly an interesting result. It may be evidence of implementation of similar strategies by traders, or just a result of data snooping.

We speculate the success of the strategy may be attributed to the pricing mechanism for cryptocurrencies being not well understood. As a new asset class, investors are still in disagreement as to where the value of a cryptocurrency is derived from. Furthermore, even the benchmarks used in the paper, cryptocurrency indexes such as the Bletchley Indexes are also relatively young. These indexes are not tradable either – financial innovations such as ETFs readily available in mainstream financial markets are not available in cryptocurrency markets. The infrastructure for cryptocurrencies still has a way to go, and as it matures profits from our strategy should decline.

However, it is worth noting the many limitations to the implementation of the proposed strategy. First of all, as a new market, liquidity in many coins beyond a fraction of the total cryptocurrencies in circulation is laughable at best. Investors may face significant slippage when buying or selling these coins. Furthermore, the lack of trading activity in these illiquid coins undermine any recorded price of the coin on websites such as Cryptocompare and Coinmarketcap. Any trading strategy dependent on price alone is vulnerable and strict consideration must be given to decide which coins are eligible for such a strategy. Lastly, in practice, shorting a cryptocurrency apart from Bitcoin (futures are available from the CME) and certain currencies[14] is difficult.

Nonetheless we conclude there is ample opportunity within cryptocurrency markets to generate profits using the proposed strategy.

[14] The Kraken exchange supports margin trading and leveraged trading https://support.kraken.com/hc/en-us/articles/227876608-Which-currency-pairs-can-I-trade-on-margin-

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Appendix

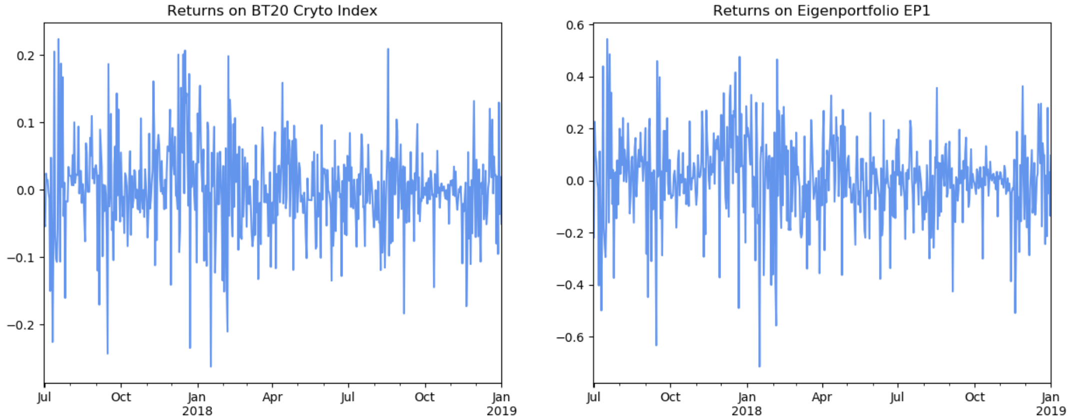

Figure 15 – Evolution of daily returns of the Bletchley 20 Index and the first eigen portfolio

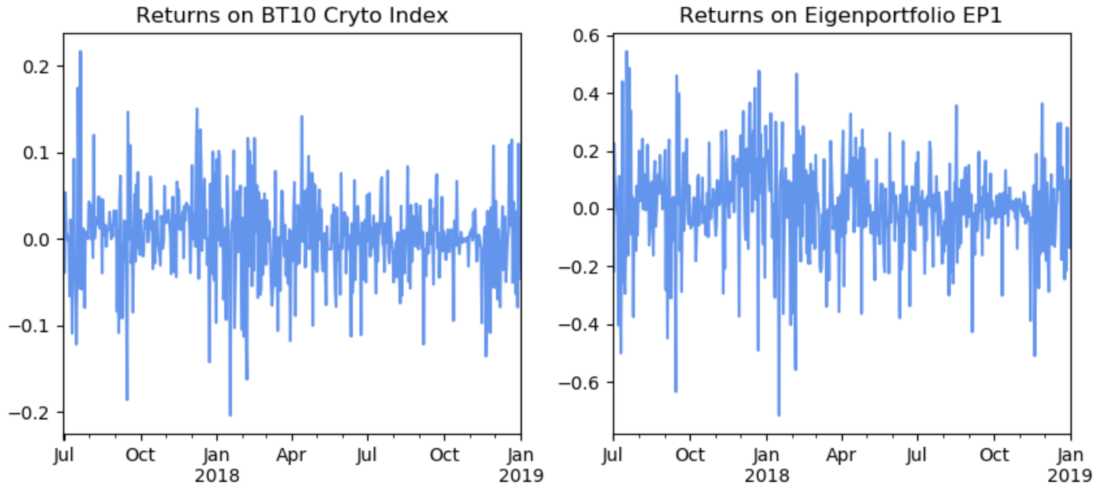

Figure 16 – Evolution of daily returns of the Bletchley 10 Index and the first eigen portfolio

Table 9 – Results from changing how often the eigenportfolio is recomputed

Varying the interval between eigenportfolio re-computation

Annual Return	PCA Window	Regression Window	# of PCS	Eigenportfolio recomputation interval
52%	180	50	5	10
40%	180	50	5	15
50%	180	50	5	20
53%	180	50	5	25
50%	180	50	5	30
42%	180	50	5	35
53%	180	50	5	40
55%	180	50	5	45
55%	180	50	5	50
46%	180	50	5	55
63%	180	50	5	60
61%	180	50	5	65
49%	180	50	5	70
51%	180	50	5	75
54%	180	50	5	80
46%	180	50	5	85

Table 10

Varying the length of the regression window with a fixed PCA window of 160

Annual Return	PCA Window	Regression Window	# of PCS	Eigenportfolio recomputation interval
11.85%	160	30	5	60
10.00%	160	35	5	60
30.78%	160	40	5	60
42.53%	160	45	5	60
62.89%	160	50	5	60
34.96%	160	55	5	60
27.68%	160	60	5	60
30.85%	160	65	5	60
26.48%	160	70	5	60
31.25%	160	75	5	60
27.71%	160	80	5	60
31.84%	160	85	5	60

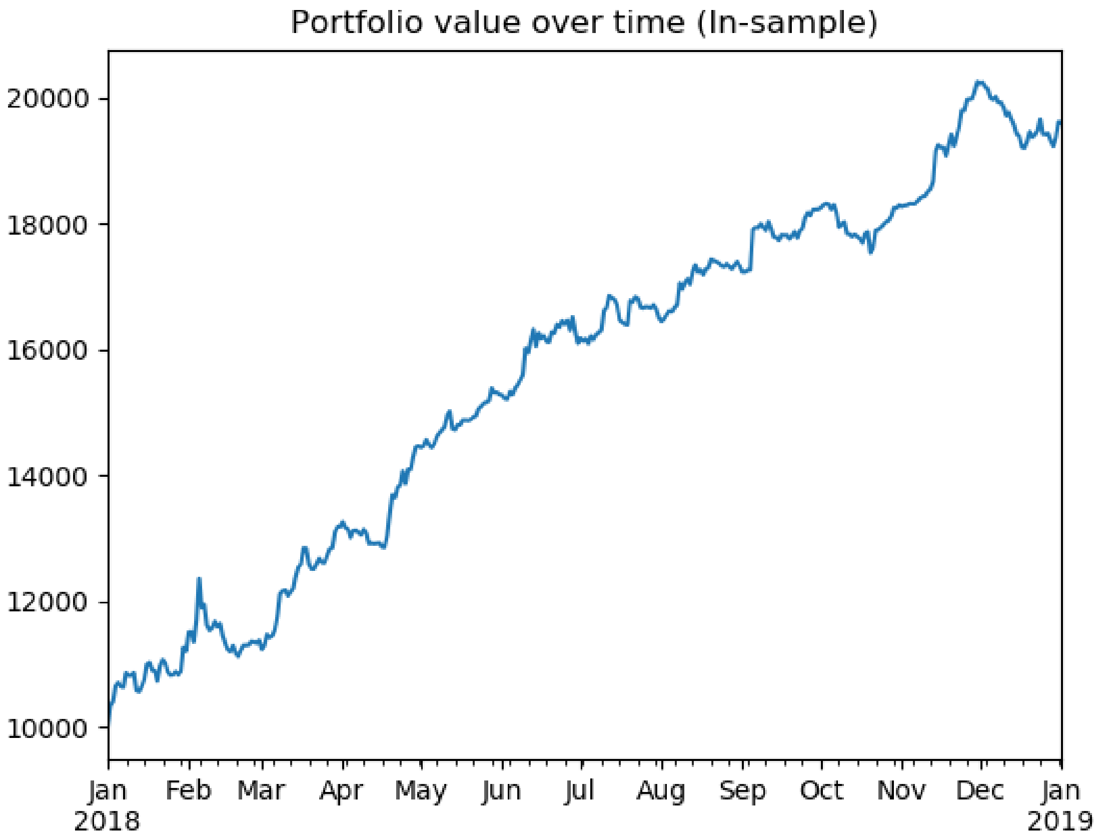

Figure 17 – A graphical depiction of the evolution of the portfolio value throughout the sample period. This portfolio corresponds to trading using a PCA window of 160 days, a regression window of 50 days, 5 principle components, $10000 in initial capital and following the optimal trading rules.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    BTC   R-squared:                       0.737
Model:                            OLS   Adj. R-squared:                  0.707
Method:                 Least Squares   F-statistic:                     24.63
Date:                Tue, 04 Jun 2019   Prob (F-statistic):           9.68e-12
Time:                        18:10:19   Log-Likelihood:                 93.607
No. Observations:                  50   AIC:                            -175.2
Df Residuals:                      44   BIC:                            -163.7
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0058      0.007     -0.866      0.391      -0.019       0.008
EP1            0.1457      0.032      4.618      0.000       0.082       0.209
EP2            0.0203      0.009      2.175      0.035       0.001       0.039
EP3            0.0079      0.010      0.816      0.419      -0.012       0.028
EP4           -0.0342      0.007     -4.701      0.000      -0.049      -0.020
EP5           -0.0505      0.006     -7.869      0.000      -0.063      -0.038
==============================================================================
Omnibus:                        0.423   Durbin-Watson:                   1.692
Prob(Omnibus):                  0.809   Jarque-Bera (JB):                0.493
Skew:                           0.202   Prob(JB):                        0.781
Kurtosis:                       2.729   Cond. No.                         6.17
==============================================================================
```

Figure 18 – Regression output for the returns of BTC in the trailing 50 days from 2018/1/1 against the returns of the first 5 eigenportfolios for the same window.