Algorithmic Trading of Crypto-Currencies

Ian Shaw
Advisor: Markus Pelger, Ph.D., Assistant Professor

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Abstract

Crypto-currencies have become the financial topic of 2017. This is due to the large price increase that is outpacing any other asset class, even in a bull market. This begs the question: can algorithmic trading boost the profits of speculation? In our investigation we look at many forms of trading algorithms, novel and traditional, and present three with their results of backtest from June 2016 to June 2017. We have found that the market, unsophisticated relative to equities and FOREX, also exhibits its own unique dynamics. These new and unexplored dynamics, combined with an already many times multiplication in value of the crypto-currencies, make excess profits difficult to generate via algorithmic trading. Though our strategies showed profit, they could not out-pace the market.

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1 Background

1.1 What are Crypto-Currencies?

Crypto-currencies began in their most recent wave with the inception of Bitcoin. Released in a white paper in 2008 under the name Satoshi Nakomoto, this block-chain protocol stems from cryptography and an undestanding of the true nature of currencies. Since then, many groups have attempted to improve upon this technology to issue their own crypto-currency in order to provide economic value. Bitcoin attempted to decentralize value in reaction to the public distrust that calcified in the wake of the financial crisis. Etherium, the second largest by market capitalization, seeks to provide currency, and through that currency a platform for blockchain applications. Potcoin, a smaller niche altcoin, attempts to provide an electronic transferable credit platform for the global marijuana industry; due to federal regulations American marijuana affiliated-businesses cannot open bank accounts and deal almost exclusively in cash. Our data set alone has 189 crypto-currencies traded against Bitcoin (BTC); all with their own reason for creation and existence; some more useful than others.

1.2 Market Dynamics

The total number of coins in this universe paired with its relatively low capitalization compared to other financial instruments, especially fiat currencies, creates fascinating market dynamics. Some of these are reminicesnt of the early post-Bretton Woods currency markets, others similar to early twentieth century U.S. equities markets, and yet others are completely novel. At the time of this writing Potcoin (POT) just underwent a pump-and-dump scheme. This works as a group of market manipulators, often organizing through open interet forums such as Reddit, put in a series of small buy orders for POT over the course of about an hour. The orders push the price up and attract speculators outside the inner group. This drives the price further and further up at an increasing pace. The inside group then quickly sells off in order to capture the synthetic profits. The sell-off drives the price down, often below previous levels.

This type of scheme is possible due to light liquidity and regulation. The relatively small group of manipulators is able to push the price up since the market is not liquid enough to aborb the orders without pushing the price. These types of actions take an incredible amount of capital in the liquid, sophisticated FOREX and U.S. Equities markets. The traditional markets are also subject to oversight scrutiny that is enforcable on the domestic and international level. Crypto-currencies, due to their architectural anonymity and somtimes untracability of regulation (depending on the currency protocol) are usually only self-regulating and often do not have a central authority. Thus unethical maniputlation is not limited by authorities, but market share.

1.3 Why Trade Algorithmically?

Crypto-Currencies are ripe for algorithmic trading due to two factors: lack of institutional money and opaque fundamentals.

The lack of large banks or hedge funds participating in the crypto-markets mean that the market itself is not crowded. Much like the early stages of any elctronic financial market, the dearth of understanding of this market means there are many instances of inefficiency which have not been smoothed by smart money activity.

The fundamentals of crypto-currencies are difficult for the outsiders to understand. The businesses represented in stock markets or the governments behind fiat currencies swing in valuation due to often intuitive fundamentals: management quality, economic conditions, etc. Crypto-currencies, on the other hand, have their fundamentals based in the workings of cryptography, the inefficies of currency markets and financial institutions, and the philosophical concept of currency itself. Thus crypto-currencies have fundamentals that are far more difficult to grasp and thus largely misunderstood. This leads market participants to not act on their understanding of the bitcoin and altcoin merits, but largely on techinical factors (price, volume, etc.) which are more accesible and interpretable.

A market with high inefficiency and reliant on techinical factors is ripe for quantitative, algorithmic strategies to profit.

2 Data

On June 26, 2017 Rami Kawach, the founder of the crypto-currency exchange Bittrex, posted a link on twitter to a google drive containing price history data [1]. These files log prices as they are updated, with granularity maxing out to one minute intervals. Each csv tracks the full history of each coin from ICO to June 25, 2017 of the exchange rate between the coin and Bitcoin (BTC), volume, and other technical components. This is the data used in this report.

2.1 Coins

In Appendix A & B you will find a tables with each of the 187 coins (as of June 25, 2017) traded on Bittrex and the first day it appeared on the Bittrex exchange to be traded against Bitcoin (BTC) by ticker. These dates vary in length from their respective Initial Coin Offering (ICO) dates. This is due to the Bittrex compliance rules which state:

> *"At Bittrex, we look for coins that have high community demand, innovations to digital currency technology, or a contribution to science or humanity. Given the demand for currency launches, we limit ourselves to only a handful a week. ... Note that we cannot list currencies where its primary purpose is to support illegal gambling, illegal drug sales, or any other activity that is illegal in our jurisdiction." [2]*

For reference, Bittrex is incorporated and operated from the United States and maintains a New York Bitlicense.

For our statistical testing, we will use the coins traded against Bitcoin since late Feburary 2016 that are also still active on the Bittrex exchange, this amounts to 99 coins. For backtesting we will use a more narrow subset.

2.2 Filtering

The data provided only provides points for every update in price, with the finest granularity of 1one minute. In order to homogenize the data frequency, we filled the dataset forward on a minutely basis. Each minute thus has an exchange rate equivalent to the last posted exchange rate.

3 Principal Component Analysis (PCA)

In order to understand the Bitcoin-based crypto-currency market, a classic first step is to execute a principal component analysis of the returns. In this way we may understand the drivers of market shift and their relation to one another. In Appendix (E) you will find a table of the results of a principal component analyis over the daily returns of the the 99 alt-coins in our data set.

This table is better interpreted in Figure (1) for the overall analysis and the coefficients of the first two principal components. Similar Graphics for the first five components can be found in Appendix (F).

For the U.S. Equities Market, this analysis is nearly identitcal to a market capitalization ranking. The results we have here are far from that. Comparing to the market capitalization table in Appendix (G), the reader can see that the PCA does not follow this order. This implies a departure from similarity to U.S. equities market dynamics.

4 Algorithm Purpose

The algorithms in this paper were designed with the intent to use the volatitlity of alt-coin exchange rates againt Bitcoin (BTC) in order to accumulate more Bitcoin. The benefits of this, as compared to the intent to gain profits denominated in USD are several: exchange structures, taxes, and legality.

'Exchange structures' is meant to encapsulate two elements: transaction fees, transaction speed. As of now, transaction costs between crypto-currencies are low. On Bittrex, the transaction costs are calculated

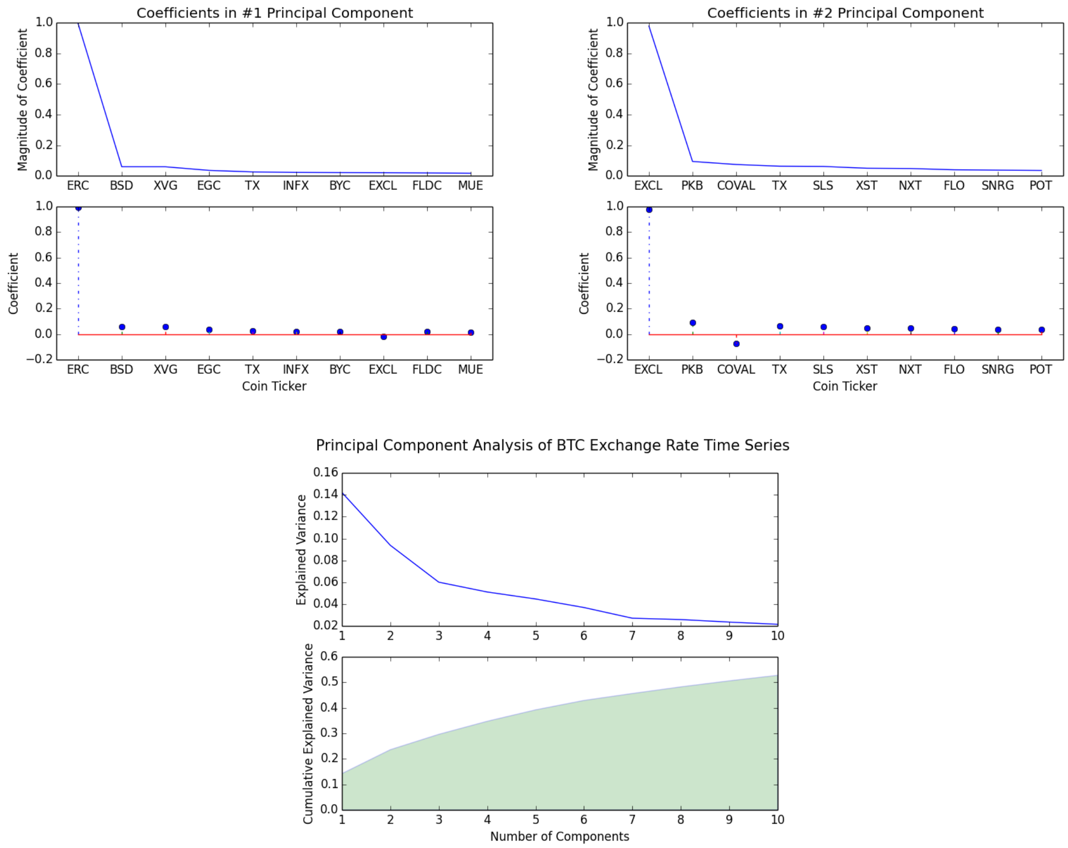


Figure 1: PCA Result Graphics

as

$$\text{transaction fee} = \text{trade amount} \times \text{purchase price} \times 0.0025$$

with no fee for deposits or withdrawls [3]. Keep in mind that Bittrex does not support transfers to USD. Certain exchanges, such at Coinbase, specialize exclusively in transferring fiat currencies into large capitalization cryptocurrencies (BTC, LTC, ETH at the time of this writing). Coinbase charges a transaction fee of "25 to 100 basis points determined by the size of your transaction, market volatitlity and length of time using Coinbase ('Exchange Rate')."[4]. Furthermore, Bittrex credits your account at the moment of transaction completion whereas Coinbase can take up to a week for transactions to process. Thus if a party maintains the thesis that Bitcoin will increase in value over time and does not need USD, it is in the party's best interest to avoid fiat exchanges for medium-frequency algorithmic trading.

The tax situation in the United States with regards to cryptocurrencies is constantly fluctuating. Yet, the ownership of Bitcoin is anonymous due to the design of the Bitcoin platform itself; thus by keeping algorithmic trading opertations within the crypto-currency space, tax complications may be avoided (for the time being).

The legality of trading, especially if trading on behalf of others such as in hedge funds and mutual funds, is complicated and often incurrs the necessity of in-house lawyers or at least maintaining a relationship with a law firm. The lack of regulation within crypto-currency space allows for this to not be the case, currently. Yet, this also indicates that there is less safety in loaning assets as there is no strong enforecemnt authority for integrity or financial responsibility. This can be seen as a benefit for scaling trading operations of trust between those who entrust assets to a financier (by minimizing costs), but also can be seen as an inhibition to devloping professionalism within the crypto-currency space.

5 Baseline

The algorithms of this paper were backtested over the five most liquid alternative cryptocurrencies: Ethereum (ETH), Litecoin (LTC), Dash (DASH), Monero (XMR), and Ripple (XRP). The time horizons for the backests vary from minute frequency to daily. Below you see a table of our baseline strategy for each coin, buy on the first day of backtest and sell on the last. The timeframe is the calander year of June 25, 2016 to June 25, 2017; the most recent full calender year available in the dataset. Below you find the table of a strategy where the data points are daily prices. The full table for all time scales (refered to as filter frequencies (Filter_Freq)) can be found in Appendix (H).

Table 1: Baseline Results of Holding Position from June 25, 2016 to June 25, 2017. Daily Data Points.

Market	Filter_Freq	Returns	No-cost Returns	Sharpe Ratio	Precision	Max Drawdown
BTC-ETH	24H	4.71	4.81	4.37	0.40	-0.69
BTC-XRP	24H	9.77	10.10	5.86	0.39	-0.70
BTC-LTC	24H	1.51	1.53	1.46	0.33	-0.58
BTC-DASH	24H	5.01	5.12	4.57	0.45	-0.58
BTC-XMR	24H	6.51	6.68	5.00	0.45	-0.74

5.1 Performance Metrics

All performance metrics are annualized, but this point is moot in the extent of this paper because all backtest were performed over one year. For this paper, algorithm performance will be measured by returns, sharpe ratio, precision, and max drawdown. Algorithm result tables will also note transaction count and no-cost returns (with zero transaction fees) so as to give a greater understanding to the quality of the signal.

The value of returns is intuitive but the other performance metrics may not be.

For the Sharpe Ratio, this can be thought of as a metric of risk adjusted returns. The Sharpe Ratio in the span of this paper is measured as:

$$\text{Sharpe } = \frac{\text{Returns - Treasury Bond Yields}}{\sigma_{\text{returns,annual}}}.$$

The use of the one year treasury bond yield is due to the lack of a stable index for the cryptocurrency market. The one year treasury bond yields for the backtest time period were 1.62%. [5]

The precision measures the quality of a algorithm signal. The structure of the algorithms outlined in this paper is to use past data to predict the returns of the upcoming time period. A positive signal would mean that the algorithm expects that entering the market for the next time period would return a profit, and a negative signal indicates that a participant should be out of the market to avoid a loss. The precision metric is defined as:

$$\text{Precision } = \frac{\text{True Positive}}{\text{True Positive - False Positive}}$$

The last major metric, max drawdown is the largest percentage loss of value of the portfolio managed by an algorithm. This metric is important to understanding the amount of leverage an investor could use when implementing an algorithm. For example, if a strategy has a max drawdown of -0.5, this would indicate at some point the portfolio lost half of its value. Thus an investor leveraged 2x would most likely face margin call. Yet, if the max drawdown is only -0.1 an investor could comfortably leverage 5x and quintuple their profits.

6 Percentage Momentum Algorithm

6.1 Economic Reasoning

The idea of momentum lies upon a combination of fundametal value shift and behavioral finance. The former is that the value of a currency changes in trends; if it were continuously mean reverting the value would never shift. The second is that many people trade attempting to capture these trends. If a speculator in crypto-currencies sees that a currency goes up 5%, they often have a personal rule to get in and let the winner ride. The same works on the back side, if they see a coin decreasing by say 10%, then the same speculator would decrease their holdings in order to avoid futher losses.

The percentage momentum strategy hopes to get in and profit from the rising price of a currency due to the buying pressure, and to empty holdings to avoid big sell offs. The question of what parameters to set depends on time horizons, transaction costs, and ability to act. All these add into the equation of whether to stay in a coin with a wider scope to avoid being shaken out due to oscillating prices inter or intra big up trends.

6.2 Algorithm

The idea behind the 'Percentage Momentum' strategy is rather simple. Buy if currently not in the market and the price rises above $X\%$ above the most recent low. Sell if currently in market and the price falls below $Y\%$ of the most recent high. You will notice that this is a long only strategy due to the lack of shorting in the cryptocurrency market.

Algorithm 1: Percentage Momentum

Data: Current Price
Result: Trade Signal
Function *Perc_momentum(price, in_market)*
  if *price* $>$ $X\% \times$ *low* & *in_market* $==$ *FALSE* **then**
    return BUY
  else if *price* $<$ $Y\% \times$ *high* & *in_market* $==$ *TRUE* **then**
    return SELL

6.3 Parameter Tuning: Walk-Forward

Due to the constantly shifting regimes of the crypto-currency market and the relatively small understanding of the market itself, walk-forward testing provides an interesting method of backtesting development. [6] This is another parameter to tune, the length of the walk forward testing. This testing procedure also provides another method by which to analyse the strengths of a strategy: showing how sensitive the strategy is to different regimes and the suseptibility of overfitting.

The procedure of the walk-forward test will be two-thirds tuning and one-third out of sample testing. Consider we wish to actively trade our strategy on the last week of May on a week long time delta. The strategy would in-sample backtest on the first two weeks of May. Then taking the most profitable parameters from those two weeks, it will out of sample backtest with those parameters on the third week of May. If this out of sample back test does not show profit, the strategy will not run. If this out of sample does show profit, the strategy will run with those parameters on the last week of May.

This allows for each walk-forward to tune the parameters of the percent increase from recent low (buy signal) and the percent decrease from recent high (sell signal). Thus the hyper-parameters to tune are the walk-forward length and the length of data observation (to act on minute, hour, or day price quotes).

The Walk-Forward Process also creates a natural trading filter, if the strategy is not profitable during the out-of sample test, the strategy does not execute. The strategy will continue to walk forward in time until a out-of-sample test is profitable. At this point the strategy will execute in real time for that same length of time as the out of sample test. For example, if the in sample test is two hours long, and the out of sample test is an hour long, then the strategy will actively run on these parameters for one hour. After an hour, if there are no open market positions. The strategy will run a parameter tuning back-test. This maintains the recency of the current trading regime in the parameters of the active strategy.

6.3.1 Parameter Re-Assessment

The strategy only updates if there are no active positions so that positions are not pre-maturely cut off of running the course of reasoning the strategy implemented the trade for. For example, if the trade is executed because the current market regime dictates that positive momentum exists on a 1% rise in price from the bottom and negative mometnum develops on a 5% dip from the top, to exit this trade prematurely could result in a loss, or an opportunity cost in profits. Furthermore, this contradictss the underlying principal of our strategy; let winners ride. There could be a corner case where a domain says to hold on to the coin for a long period of time because of a backtesting window that only caputre a strong, consistent rise in price. This would then cause a coin to be consistently held even while price drops, and halt the strategy from updating.

In the case that no good parameters are found, the strategy has a built in delay of a 10% data turnover before running another parameter search. This is to preserve computational resources. Furthermore, this allows the regime of backtesting to change over enough for the probability of finidnig good parameters to increase.

6.4 Backtesting

The results of the backtest can be seen in the table below. The backtest was excuted on minute data with 30 minute in-sample time windows (with minute data). Keep in mind, the in sample part of the walk-forward back test is twice as long as the in sample back test.

Table 2: Walk-Forward Momentum Algorithm Results June 25, 2016 to June 25, 2017

Market	Returns	Transaction Count
BTC-ETH	6.11	17
BTC-XRP	10.64	35
BTC-LTC	1.20	11
BTC-DASH	5.39	15
BTC-XMR	2.19	18

The results are interesting to show how difficult it is for a strategy to develop excess returns, as the baseline returns are so high on their own. Furthermore, one can see that the transaction count is low, below one round-trip transaction per week for even the most active strategy. This is due to the high upward momentum of all the currency pairs, causing the strategy to hold on for long periods of time.

The associated plots of each can also be seen in the Appendix (I). In these plots the upper sublplots has the price rexchange rate in dotted yellow on the left and right axis, and the exchanges as lines in green (profitable) and red (loss).

What can be concluded is that the strategy is profitable, yet not acitve over the backtesting window. This implies a lack of capturing alpha, more a chance ability to ride upward trends. Therefore we conclude this strategy, though profitable, not to be actionable out of backtesting.

6.5 Further Discussion

The strategy was run with a 30 minute in-sample period with one minute granularity as this is the highest-frequency and granularity this strategy can afford with the minute data provided by Bittrex. Longer in-sample tests of 4 weeks and 2 weeks over the same one year period with 1 hour data granularity were not profitable.

6.5.1 Future Work on Walk Forward Momentum

Despite successful backtesting results, there is always thoughts on how to improve.

Track the profitable momentum parameter pairs. Understanding the parameters that lead to profitable and unprofitable trades could shed light on the behavior of the cryptocurrency markets and narrow the set of possible parameters the strategy should act upon in the future.

Investigating a more time-tractable method of searching of better parameters could be a combination fo mahine learning techniques and more computational power. Could allow for more granular options for the optimal enter/exit parameters, a hyperparameter of the backtest length as a multiple of the time horizon (this was held to 2 in our testing), and the time horizon itself as a hyperparameter the strategy could itself alter (manually ran on separate time horizons in our experiments).

Shorting in the strategy. Currently, the crypto-currency market is in its infancy. Derivatives and shorting contracts are beginning to be devloped, but at the time of this writing they are not wide-spread. The inherent difficulty with shorting crypto-currencies us ther decentralized nature. Shorting contracts inherently necessitate some time of enforcable authority, yet crypto-currencies are largely based on the concept of self-regulation. Thus the best current, intuitive, solution are peer-to-peer loans in order to execute short side plays. Yet, they are slow to execute, usually on at least a three day lag for the BitFinex platform. This is not useful on the medium frequency our walk-forward momentum algorithm intends to operate.

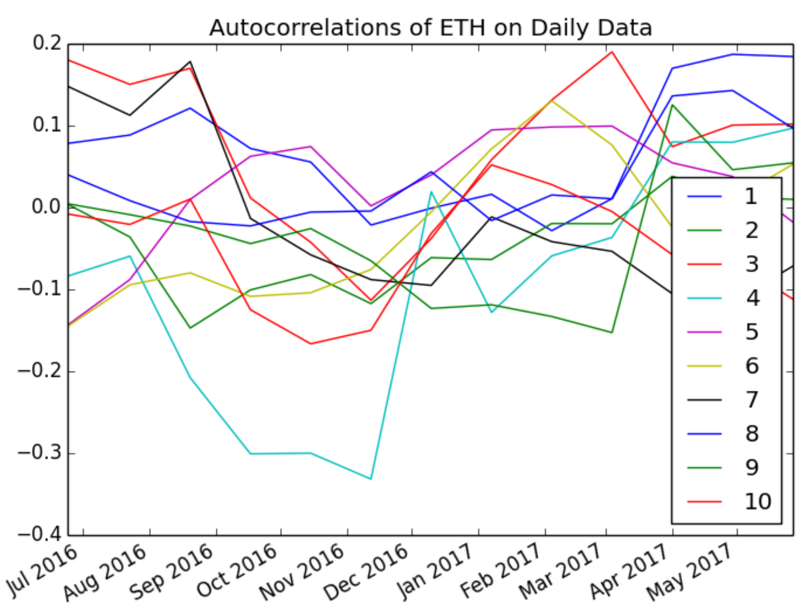
7 Layered Autoregressive (AR) Algorithm

7.1 Economic Intuition

The intent of an autoregressive strategy is to capture the momentum and mean reverion of an asset. The length of the regression is a tricky decision, as the amount of infuence a given period has on the current period decays exponentially with time. To choose too long of a regression would distract and overfit the model, yet there are fluctuating decays of the past. For example, this Friday's return will may have some correlation with Wednesday's return, but possibly more correlation with last Friday's return. Though this is five days further in the past, human actors reflect patterns tied to the calander.

7.2 Correlations

The autocorrelations of crypto-currencies appear to vary quite widly. See the figure below of the monthly-assesed autocorrelations for ETH.



As you can see, the autrocorrelations not only change with magnitude over time, but even sign. This means at some points the 2-lag return sometime has a positive, and other times negative, corrrelation with the current return. This is curious and begs further investigation as immedeate intuition provides no answer.

7.3 Algorithm

The strategy autoregresses the previous 10 time step returns, with a training period of 30 time steps (15 or 30 days in our tests). Then using logistic regression with inputs of predicted returns and the rolling sigma of returns (standard deviation, a measure of volatility) and rolling normalized trading volume of the previous time step, the strategy assess whether the returns are to be positive. The hope of the layered regression technique is to filter the autoregressive prediction with the volume and volatility expected for the next time step.

An added element of boosting is involved. The strategy only enters the market if it expects the next time step to be profitable beyond transaction costs. The boosted aspect is that once in the market (thus already accepting transaction costs), the strategy will remain within the market so long as it expects the next period to have positive returns.

Algorithm 2: Layered Regression Strategy

```
Data: Returns, Rolling Returns Sigma, Rolling Normalized Volume
Result: Trade Signal
Function LayeredRegrssion(date)
    PredictedReturns = AutoRegression(returns, lag = 10, train = date - 30 * FilterFreq)
    if InMarket then
        NextReturns01 = NextReturn.apply(If > 0: 1, Else: 0)
    else
        NextReturns01 = NextReturn.apply(If > TransactionCosts: 1, Else: 0)
    InMarketPred = LogisticRegresstion(y = NextReturns01, x= PredictedReturns,
     ReturnsSigma, NormalizedVolume, train = date - 30 * FilterFreq)
    if InMarketPred == 1 then
        return InMarket = True
    else
        return InMarket = False
```

7.4 Results

This strategy only yields profitability on daily and half-day data points. The results are found in the table below.

Table 3: Results of Layered AR Strategy with Backtest from June 25, 2016 to June 25, 2017.

Market	Filter_Freq	Returns	Sharpe Ratio	Max Drawdown	Transaction Count	No-cost Returns
BTC-ETH	12H	2.84	3.29	-0.45	123.0	6.56
BTC-ETH	24H	-0.55	-0.65	-0.33	61.0	-0.41
BTC-XRP	12H	0.04	0.02	-0.51	121.0	0.82
BTC-XRP	24H	1.94	1.36	-0.46	56.0	3.40
BTC-LTC	12H	-0.46	-0.58	-0.26	136.0	-0.06
BTC-LTC	24H	0.24	0.27	-0.33	61.0	0.67
BTC-DASH	12H	1.11	1.08	-0.47	117.0	3.03
BTC-DASH	24H	1.10	1.29	-0.54	71.0	2.11
BTC-XMR	12H	-0.35	-0.31	-0.55	132.0	0.26
BTC-XMR	24H	4.64	4.48	-0.41	56.0	11.34

As you can see, thought the majority of these instances are profitable, they are a far cry from out peeforming a buy-and-hold strategy.

7.5 Other Ideas

Other additions to the autoregressive strategy we explored were:

- Have Monthy rather than continuous updating of regression coefficients

- Reverse the predictions. Have the default be in the market, and only exit the market when the strategy expects the next period's losses to be worse than the transaction costs of exit and enter. The thought was that with such an upward trending market, the default should be in the market.
- Incorporate moving averages in the autoregression. An ARMA model.

All these techiniques did not add profit to our strategy, so they were not included in this paper.

8 Statistical Arbitrage Algorithm

8.1 Economic Reasoning

In the cryptocurrency markets, unlike FOREX, there is not a traded pairing for every two currencies. For example, a market participant can trade 'BTC-DASH' and 'BTC-XRP' but at the time of this writing Bittrex did not support a 'DASH-XRP' market. Therefore, there is a window of opportunity to capitalize upon the inter-play of two correlated currencies, similar to correlated equities in the U.S Stock market.
The algorithm's intution is to look at the correlation of two currencies, and to notice when they begin to deviate from that correlation. Under the hypothesis that the typical correlation will be reverted to, the algorithm enters the market in a way that profits on this reversion. This correlation separation does not happen on smaller time scales, so the algorithm was backtested on only the loger time filtered data.
For an explaination of the algorithm, see the paper "Statistical Arbitrage in the U.S. Equities Market" by Avellaneda and Lee. [7]

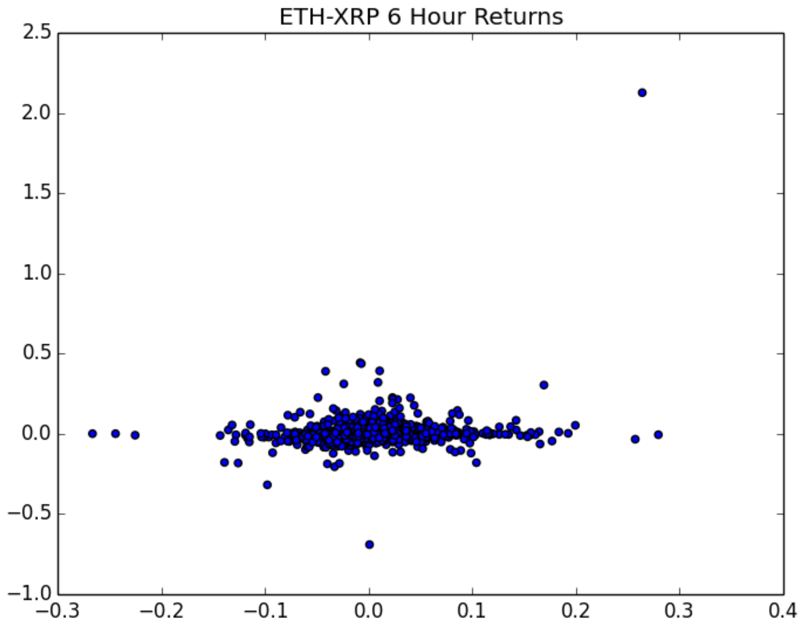
8.2 Results

You can see from the table below that the results of this strategy are not on the extraordinarly order of the baseline.

Table 4: Statistical Arbitrage Strategy Results from June 25, 2016 to June 25, 2017. Daily Data Points.

Pair	Filter Freq	Returns	Sharpe Ratio	Max Drawdown	Transaction Count	No-cost Returns
ETH,XRP	24H	0.23	3.46e-01	-0.36	10	0.27
ETH,LTC	24H	0.05	7.04e-02	-0.48	13	0.09
ETH,XMR	24H	0.02	3.85e-03	-0.74	11	0.05
LTC,XRP	24H	0.58	7.60e-01	-0.47	10	0.62
LTC,XMR	24H	0.97	1.11e+00	-0.66	10	1.02
DASH,ETH	24H	0.52	6.62e-01	-0.56	13	0.57
DASH,XRP	24H	0.15	1.94e-01	-0.54	10	0.18
DASH,LTC	24H	0.63	8.05e-01	-0.61	13	0.69
DASH,XMR	24H	-0.22	-3.01e-01	-0.71	14	-0.20
XMR,XRP	24H	0.56	7.18e-01	-0.57	8	0.60

Most notably, the round trip transactions are all less than about one per month. This is due to poor correlation of any of the selected currencies. This low operational tempo is due to the sub-par statistical foundation in these currencies. As you can see in the plot below, even the pair with the highest correlation (0.9 for ETH and XRP on 6 hour data points), is due to an excessive amount of zero value returns. Without these zeroes, the correlation would be much lower. Thus though the strategy is profitable, it does not outpace investing in either coin on their own.



The full results of the strategy can be found in Appendix (J). What this analysis shows though is that the high market-cap cryptocurrencies are not correlated in a way that is immedeately profitable beyond simple investing.

9 Conclusion

The recent rise in vaue of cryptocurrencies ahs drawn the attention of the public at large. This rise has been not only consistently positive. but meteorically so. From June 2016 to June 2017 the top five cryptocurrencies by market capitalization have exploded in value in such a way that smart money wants to pile in. What we have found is that conventional algorithmic trading strategies cannot outpace a simple invesitng strategy of buy-and-hold.

10 Future Work

There are always those items we wished we had more time, more data, and more computational ability to which to apply. Here are a few of those things.

- Compare algorithm perfromace on crypto-currencies with US Equities and FOREX markets to gain a comparative understanding of the crypto-currency market
- Analyze the algorithm performance over diffrent time periods to understand the shifts in dynamics of the cryptocurrency markets
- Fit GARCH, ARCH, and ARIMA models to the cryptocurrency market
- Explore the possibilities of leading and lagging cryptocurrencies
- Explore if there is predictive information from other assets classes for the movements of the crypto-currency markets
- Days before this paper was submitted, the Chicago Mercantile Exchange (CME) began selling Bitcoin Futures. This alters the dynamics of the markets, while opening up another insturment for speculators

and investors. Though the strategies in this paper trade on top of Bitcoin, there may be opportunities in the new space.

This is all to say there are numerous investigations to launch into the new market of cryptocurrencies. These can be transplanted from more established markets of foreign exchange and equities, or even completely new with the novel dynamics of this unexplored world.

Appendices

A Coins Traded on Bittrex, Alphabetical by Ticker

Table 5: Each Cryptocurrency Traded on Bittrex Before June 25, 2017. Sorted Alphabeticlaly by Ticker.

Ticker	Listed	Ticker	Listed	Ticker	Listed	Ticker	Listed
1ST	06/06/2017	DMD	05/01/2015	LBC	07/05/2016	SEQ	09/23/2016
2GIVE	05/16/2016	DOGE	02/14/2014	LGD	04/19/2017	SHIFT	10/11/2016
8BIT	04/18/2015	DOPE	10/17/2014	LMC	02/19/2017	SIB	02/18/2017
ABY	10/31/2014	DRACO	07/23/2016	LSK	05/24/2016	SJCX	02/15/2015
AEON	07/31/2015	DTB	04/01/2017	LTC	03/07/2014	SLR	03/23/2014
AGRS	11/10/2015	DYN	03/23/2017	LUN	04/30/2017	SLS	01/21/2016
AMP	11/04/2015	EBST	09/15/2016	MAID	01/19/2016	SNGLS	10/02/2016
ANS	10/26/2016	EDG	04/18/2017	MEME	04/01/2016	SNRG	06/03/2015
ANT	05/17/2017	EFL	03/20/2014	MLN	03/15/2017	SPHR	05/18/2015
APX	05/02/2017	EGC	01/18/2016	MONA	04/19/2014	SPR	12/19/2014
ARDR	10/13/2016	EMC	01/06/2016	MUE	04/09/2015	START	06/14/2014
ARK	03/21/2017	EMC2	03/15/2014	MUSIC	03/27/2017	STEEM	04/17/2016
AUR	03/24/2014	ENRG	05/12/2014	MYR	03/16/2014	STRAT	08/10/2016
BAT	06/03/2017	ERC	05/10/2014	MYST	06/19/2017	SWIFT	10/03/2014
BAY	11/18/2014	ETC	07/26/2016	NAUT	05/12/2014	SWT	03/08/2017
BCY	09/10/2015	ETH	08/14/2015	NAV	07/08/2014	SYNX	08/25/2016
BITB	02/15/2015	EXCL	09/28/2014	NBT	04/08/2015	SYS	08/17/2014
BLITZ	11/13/2014	EXP	09/16/2015	NEOS	08/20/2014	THC	05/01/2014
BLK	03/16/2014	FAIR	12/12/2014	NLG	04/05/2014	TIME	03/09/2017
BLOCK	10/29/2014	FCT	01/09/2016	NMR	06/22/2017	TKN	05/08/2017
BNT	06/22/2017	FLDC	02/24/2015	NXC	04/17/2017	TKS	03/23/2017
BRK	07/08/2016	FLO	03/11/2015	NXS	01/25/2015	TRIG	09/08/2016
BRX	07/10/2016	FTC	02/17/2014	NXT	03/07/2014	TRST	04/19/2017
BSD	02/17/2016	GAM	05/06/2015	OK	05/30/2015	TRUST	07/07/2014
BTA	11/20/2015	GAME	12/24/2014	OMNI	11/03/2015	TX	09/02/2015
BTCD	07/14/2014	GBG	02/12/2017	PDC	06/02/2016	UBQ	02/08/2017
BTS	11/24/2014	GBYTE	04/13/2017	PINK	07/29/2014	UNB	08/25/2016
BURST	09/16/2014	GCR	08/24/2015	PIVX	03/02/2016	UNO	07/23/2014
BYC	11/03/2014	GEO	02/21/2015	PKB	06/03/2015	VIA	07/18/2014
CANN	08/10/2014	GLD	03/23/2014	POT	03/12/2014	VOX	01/02/2016
CFI	06/19/2017	GNO	05/01/2017	PPC	02/17/2014	VRC	05/13/2014
CLAM	04/19/2015	GNT	04/17/2017	PTC	03/27/2014	VRM	09/16/2016
CLOAK	06/04/2014	GOLOS	01/19/2017	PTOY	06/18/2017	VTC	02/17/2014
CLUB	12/18/2015	GRC	02/27/2015	QRL	06/10/2017	VTR	12/19/2014
COVAL	01/22/2015	GRS	04/03/2014	QTL	06/29/2014	WAVES	06/20/2016
CPC	07/25/2015	GUP	04/30/2017	QWARK	03/05/2017	WINGS	04/26/2017
CRB	06/13/2017	HKG	02/02/2017	RADS	01/26/2016	XAUR	09/25/2016
CRW	03/06/2017	HMQ	05/10/2017	RBY	04/05/2014	XBB	06/01/2014
CURE	05/13/2014	INCNT	04/04/2017	RDD	02/25/2014	XCP	02/14/2015
DAR	12/22/2016	INFX	10/03/2015	REP	10/07/2016	XDN	06/21/2014
DASH	03/16/2014	IOC	07/29/2014	RISE	06/24/2016	XEM	04/10/2015
DCR	02/09/2016	ION	02/19/2017	RLC	04/27/2017	XLM	11/18/2015
DGB	08/20/2014	IOP	12/22/2016	SBD	07/09/2016	XMG	11/10/2014
DGD	06/14/2016	KMD	02/11/2017	SC	05/23/2017	XMR	06/04/2014
		KORE	06/17/2014	SEC	02/13/2016	XRP	12/22/2014

Ticker	Listed
XST	07/09/2014
XVC	03/12/2016
XVG	02/17/2016
XWC	04/14/2014
XZC	10/20/2016
ZCL	11/15/2016
ZEC	10/28/2016
ZEN	06/05/2017

B Coins Traded on Bittrex, Chronological by First Listing

Table 6: Each Cryptocurrency Traded on Bittrex Before June 25, 2017. Sorted Chronologically by date of Initial Coin Offering (ICO).

Ticker	Listed	Ticker	Listed	Ticker	Listed	Ticker	Listed
DOGE	02/14/2014	SYS	08/17/2014	EXP	09/16/2015	SHIFT	10/11/2016
PPC	02/17/2014	NEOS	08/20/2014	INFX	10/03/2015	ARDR	10/13/2016
VTC	02/17/2014	DGB	08/20/2014	OMNI	11/03/2015	XZC	10/20/2016
FTC	02/17/2014	BURST	09/16/2014	AMP	11/04/2015	ANS	10/26/2016
RDD	02/25/2014	EXCL	09/28/2014	AGRS	11/10/2015	ZEC	10/28/2016
LTC	03/07/2014	SWIFT	10/03/2014	XLM	11/18/2015	ZCL	11/15/2016
NXT	03/07/2014	DOPE	10/17/2014	BTA	11/20/2015	DAR	12/22/2016
POT	03/12/2014	BLOCK	10/29/2014	CLUB	12/18/2015	IOP	12/22/2016
EMC2	03/15/2014	ABY	10/31/2014	VOX	01/02/2016	GOLOS	01/19/2017
BLK	03/16/2014	BYC	11/03/2014	EMC	01/06/2016	HKG	02/02/2017
MYR	03/16/2014	XMG	11/10/2014	FCT	01/09/2016	UBQ	02/08/2017
DASH	03/16/2014	BLITZ	11/13/2014	EGC	01/18/2016	KMD	02/11/2017
EFL	03/20/2014	BAY	11/18/2014	MAID	01/19/2016	GBG	02/12/2017
GLD	03/23/2014	BTS	11/24/2014	SLS	01/21/2016	SIB	02/18/2017
SLR	03/23/2014	FAIR	12/12/2014	RADS	01/26/2016	ION	02/19/2017
AUR	03/24/2014	SPR	12/19/2014	DCR	02/09/2016	LMC	02/19/2017
PTC	03/27/2014	VTR	12/19/2014	SEC	02/13/2016	QWARK	03/05/2017
GRS	04/03/2014	XRP	12/22/2014	BSD	02/17/2016	CRW	03/06/2017
NLG	04/05/2014	GAME	12/24/2014	XVG	02/17/2016	SWT	03/08/2017
RBY	04/05/2014	COVAL	01/22/2015	PIVX	03/02/2016	TIME	03/09/2017
XWC	04/14/2014	NXS	01/25/2015	XVC	03/12/2016	MLN	03/15/2017
MONA	04/19/2014	XCP	02/14/2015	MEME	04/01/2016	ARK	03/21/2017
THC	05/01/2014	SJCX	02/15/2015	STEEM	04/17/2016	DYN	03/23/2017
ERC	05/10/2014	BITB	02/15/2015	2GIVE	05/16/2016	TKS	03/23/2017
NAUT	05/12/2014	GEO	02/21/2015	LSK	05/24/2016	MUSIC	03/27/2017
ENRG	05/12/2014	FLDC	02/24/2015	PDC	06/02/2016	DTB	04/01/2017
VRC	05/13/2014	GRC	02/27/2015	DGD	06/14/2016	INCNT	04/04/2017
CURE	05/13/2014	FLO	03/11/2015	WAVES	06/20/2016	GBYTE	04/13/2017
XBB	06/01/2014	NBT	04/08/2015	RISE	06/24/2016	GNT	04/17/2017
CLOAK	06/04/2014	MUE	04/09/2015	LBC	07/05/2016	NXC	04/17/2017
XMR	06/04/2014	XEM	04/10/2015	BRK	07/08/2016	EDG	04/18/2017
START	06/14/2014	8BIT	04/18/2015	SBD	07/09/2016	LGD	04/19/2017
KORE	06/17/2014	CLAM	04/19/2015	BRX	07/10/2016	TRST	04/19/2017
XDN	06/21/2014	DMD	05/01/2015	DRACO	07/23/2016	WINGS	04/26/2017
QTL	06/29/2014	GAM	05/06/2015	ETC	07/26/2016	RLC	04/27/2017
TRUST	07/07/2014	SPHR	05/18/2015	STRAT	08/10/2016	GUP	04/30/2017
NAV	07/08/2014	OK	05/30/2015	UNB	08/25/2016	LUN	04/30/2017
XST	07/09/2014	PKB	06/03/2015	SYNX	08/25/2016	GNO	05/01/2017
BTCD	07/14/2014	SNRG	06/03/2015	TRIG	09/08/2016	APX	05/02/2017
VIA	07/18/2014	CPC	07/25/2015	EBST	09/15/2016	TKN	05/08/2017
UNO	07/23/2014	AEON	07/31/2015	VRM	09/16/2016	HMQ	05/10/2017
PINK	07/29/2014	ETH	08/14/2015	SEQ	09/23/2016	ANT	05/17/2017
IOC	07/29/2014	GCR	08/24/2015	XAUR	09/25/2016	SC	05/23/2017
CANN	08/10/2014	TX	09/02/2015	SNGLS	10/02/2016	BAT	06/03/2017
		BCY	09/10/2015	REP	10/07/2016	ZEN	06/05/2017

Ticker	Listed
1ST	06/06/2017
QRL	06/10/2017
CRB	06/13/2017
PTOY	06/18/2017
MYST	06/19/2017
CFI	06/19/2017
BNT	06/22/2017
NMR	06/22/2017

C Currency Value Change: Sorted Alphabetically

Table 7: Returns Denominated in Bitcoin (BTC) of each Cryptocurrency Traded Against BTC on Bittrex Exchange from June 25, 2016 to June 25, 2017. Sorted Alphabetically by Ticker.

Ticker	Return (x100%)	Ticker	Return (x100%)	Ticker	Return (x100%)
ABY	9.700000	GEO	7.346579	XLM	4.140351
AEON	27.832780	GLD	1.093838	XMG	4.019593
AGRS	-0.102644	GRC	2.393514	XMR	6.951637
AMP	1.688146	GRS	9.506711	XRP	9.393237
AUR	-0.170079	INFX	7.480543	XST	5.563636
BAY	31.727273	IOC	5.393636	XVG	48.000000
BCY	2.704987	KORE	37.353134	XWC	10.100000
BITB	29.600000	LTC	1.637317		
BLITZ	23.943284	MAID	0.666720		
BLK	3.224353	MONA	1.846961		
BLOCK	23.177776	MUE	245.800000		
BSD	22.072072	NAV	34.724000		
BTCD	13.212450	NBT	0.189393		
BTS	18.884740	NEOS	84.035622		
BURST	32.178571	NLG	14.224199		
BYC	0.128314	NXS	19.760729		
CANN	6.344538	NXT	2.788863		
CLAM	1.521196	OK	21.524510		
CLOAK	15.775508	OMNI	9.733335		
CLUB	-0.195472	PINK	26.272727		
COVAL	1.151515	PKB	13.592548		
CPC	-0.481525	POT	40.944000		
CURE	1.595700	PPC	1.164233		
DASH	5.014626	PTC	25.958333		
DCR	5.829755	RADS	5.766862		
DGB	19.000000	RBY	-0.110532		
DMD	1.658251	RDD	10.142857		
DOGE	1.456522	SLR	-0.550913		
DOPE	24.909091	SLS	28.140482		
EFL	1.443609	SNRG	28.833512		
EGC	47.784722	SPHR	24.984252		
EMC	1.407951	SPR	5.961482		
EMC2	65.511111	START	0.248415		
ENRG	42.390411	SWIFT	2.141174		
ERC	21.169279	SYS	7.408840		
ETH	4.875478	THC	20.842105		
EXCL	211.568421	TRUST	12.162393		
EXP	2.633641	TX	17.180924		
FAIR	2.756757	USDT	-0.765269		
FCT	6.630172	VIA	47.498829		
FLDC	39.172414	VOX	-0.635224		
FLO	7.349515	VRC	1.583632		
FTC	-0.411800	VTC	6.332606		
GAM	15.765217	VTR	15.937853		
GAME	24.460758	XCP	1.707549		
GCR	1.644107	XDN	8.000000		
		XEM	7.457143		

D Currency Value Change: Sorted by Return

Table 8: Returns Denominated in Bitcoin (BTC) of each Cryptocurrency Traded Against BTC on Bittrex Exchange from June 25, 2016 to June 25, 2017. Sorted by Ascending Retrun.

Ticker	Return (x100%)	Ticker	Return (x100%)	Ticker	Return (x100%)
USDT	-0.765269	FCT	6.630172	VIA	47.498829
VOX	-0.635224	XMR	6.951637	EGC	47.784722
SLR	-0.550913	GEO	7.346579	XVG	48.000000
CPC	-0.481525	FLO	7.349515	EMC2	65.511111
FTC	-0.411800	SYS	7.408840	NEOS	84.035622
CLUB	-0.195472	XEM	7.457143	EXCL	211.568421
AUR	-0.170079	INFX	7.480543	MUE	245.800000
RBY	-0.110532	XDN	8.000000		
AGRS	-0.102644	XRP	9.393237		
BYC	0.128314	GRS	9.506711		
NBT	0.189393	ABY	9.700000		
START	0.248415	OMNI	9.733335		
MAID	0.666720	XWC	10.100000		
GLD	1.093838	RDD	10.142857		
COVAL	1.151515	TRUST	12.162393		
PPC	1.164233	BTCD	13.212450		
EMC	1.407951	PKB	13.592548		
EFL	1.443609	NLG	14.224199		
DOGE	1.456522	GAM	15.765217		
CLAM	1.521196	CLOAK	15.775508		
VRC	1.583632	VTR	15.937853		
CURE	1.595700	TX	17.180924		
LTC	1.637317	BTS	18.884740		
GCR	1.644107	DGB	19.000000		
DMD	1.658251	NXS	19.760729		
AMP	1.688146	THC	20.842105		
XCP	1.707549	ERC	21.169279		
MONA	1.846961	OK	21.524510		
SWIFT	2.141174	BSD	22.072072		
GRC	2.393514	BLOCK	23.177776		
EXP	2.633641	BLITZ	23.943284		
BCY	2.704987	GAME	24.460758		
FAIR	2.756757	DOPE	24.909091		
NXT	2.788863	SPHR	24.984252		
BLK	3.224353	PTC	25.958333		
XMG	4.019593	PINK	26.272727		
XLM	4.140351	AEON	27.832780		
ETH	4.875478	SLS	28.140482		
DASH	5.014626	SNRG	28.833512		
IOC	5.393636	BITB	29.600000		
XST	5.563636	BAY	31.727273		
RADS	5.766862	BURST	32.178571		
DCR	5.829755	NAV	34.724000		
SPR	5.961482	KORE	37.353134		
VTC	6.332606	FLDC	39.172414		
CANN	6.344538	POT	40.944000		
		ENRG	42.390411		

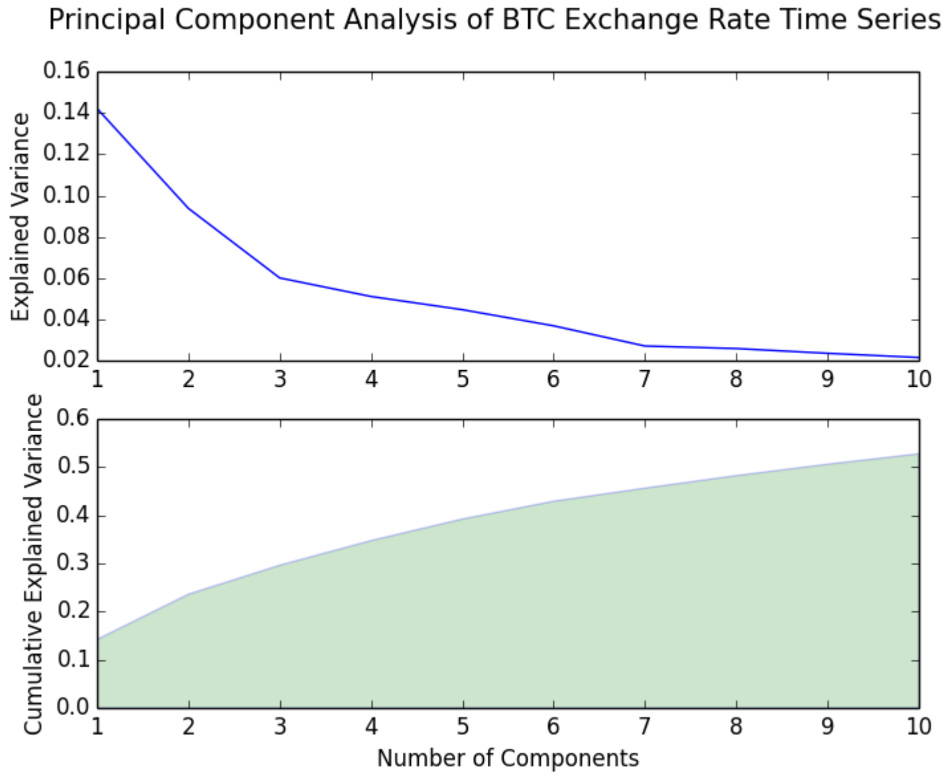
E PCA Table

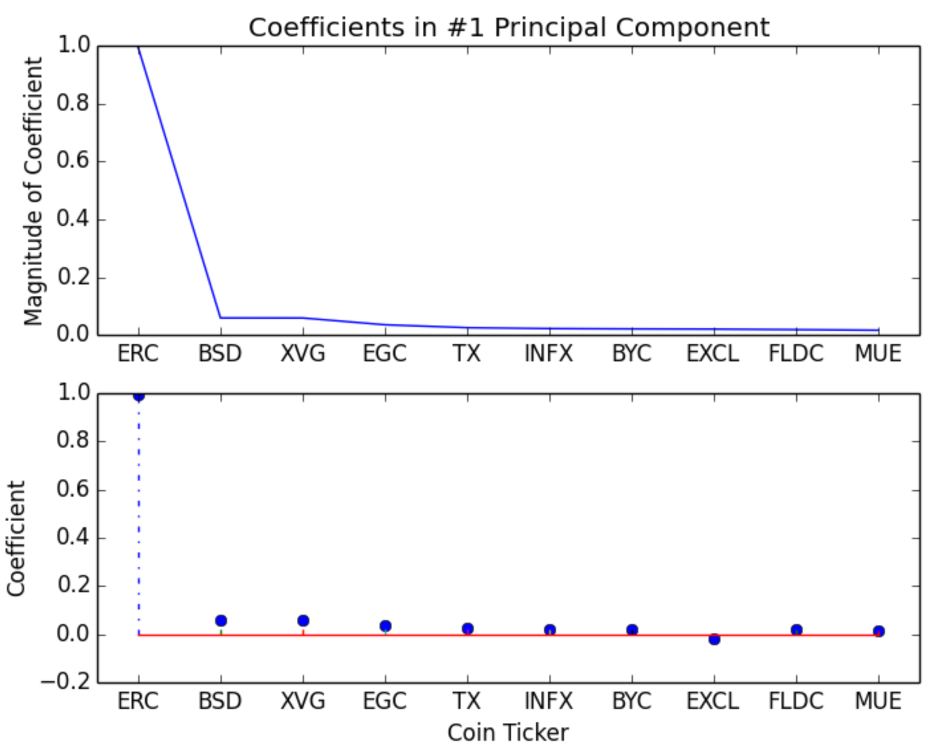
Table 9: PCA Results.

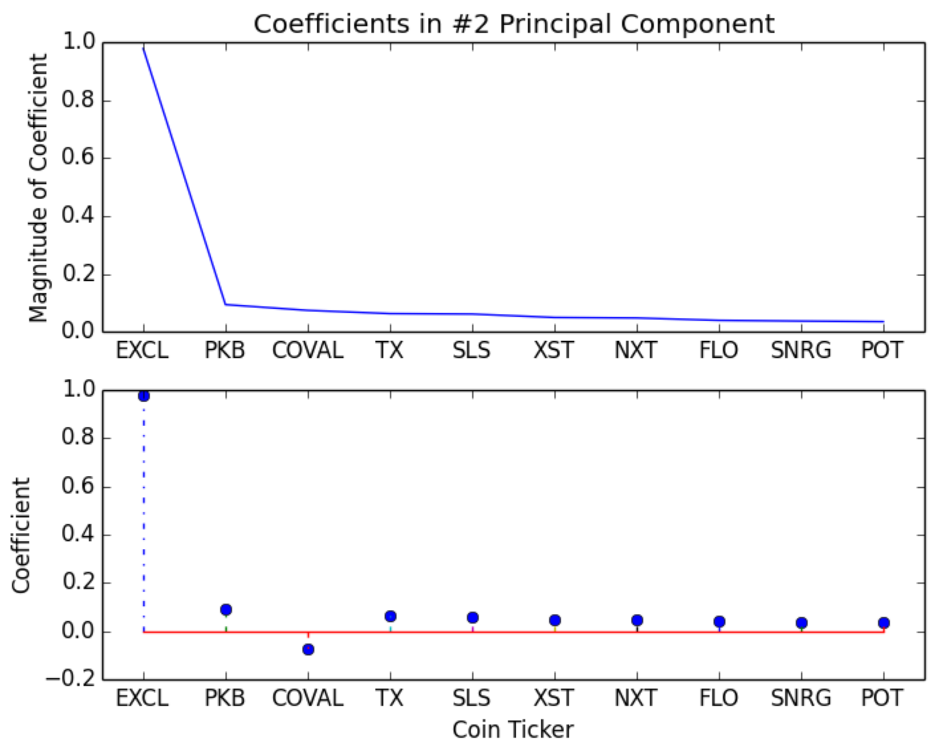
	1	2	3	4	5	6	7	8	9	10
BITB	0.00	0.01	0.16	-0.07	-0.13	0.01	0.05	-0.04	-0.09	0.15
BLITZ	-0.00	0.03	0.06	-0.03	-0.01	0.04	-0.03	0.02	-0.16	-0.03
BSD	0.06	-0.00	0.07	-0.01	-0.04	0.14	-0.07	0.03	-0.08	-0.20
BTCD	-0.00	-0.01	0.02	-0.00	-0.00	0.00	0.71	-0.20	0.04	-0.14
BYC	0.02	0.02	0.03	0.00	-0.03	-0.00	-0.02	-0.01	-0.03	-0.06
CLOAK	-0.01	0.01	0.08	-0.06	-0.11	0.05	-0.03	0.01	0.00	-0.15
COVAL	0.00	-0.07	0.04	-0.02	-0.02	0.11	0.03	-0.01	0.01	-0.00
CURE	0.01	0.03	0.32	0.43	-0.01	-0.06	-0.06	-0.03	0.02	0.02
DGB	0.00	0.01	0.04	0.00	-0.01	0.11	-0.05	0.00	-0.16	0.03
DOPE	-0.01	0.01	0.40	-0.27	0.72	-0.09	-0.05	-0.01	0.13	0.10
EGC	0.04	0.02	0.12	-0.07	-0.11	-0.05	0.03	-0.06	-0.23	-0.05
EMC2	0.00	-0.01	0.08	0.05	-0.00	0.08	0.06	-0.02	-0.12	0.19
ERC	0.99	0.02	-0.03	-0.01	0.02	-0.04	0.00	-0.01	0.01	-0.01
EXCL	-0.02	0.98	-0.11	0.04	0.04	0.01	0.00	-0.03	0.05	-0.01
FLDC	0.02	0.03	0.43	0.62	-0.05	-0.02	-0.02	0.00	0.08	-0.04
NEOS	0.01	0.03	0.07	-0.04	-0.05	0.06	0.24	0.91	0.01	0.09
NXT	0.00	0.05	0.02	-0.02	-0.02	0.02	0.02	-0.01	-0.09	-0.02
OMNI	-0.01	-0.01	-0.01	-0.02	0.02	0.01	0.08	-0.06	-0.10	-0.06
PINK	-0.00	-0.01	0.12	0.04	0.03	0.07	0.00	-0.03	-0.16	-0.10
PKB	0.01	0.09	0.34	-0.35	-0.30	-0.19	-0.12	0.06	0.15	-0.17
POT	-0.01	0.03	0.08	-0.04	0.08	0.01	-0.01	0.02	-0.03	-0.06
SNRG	0.00	0.04	0.33	-0.25	-0.37	-0.22	0.06	-0.07	0.29	0.29
SPHR	0.01	0.02	0.03	0.01	0.03	-0.01	0.49	-0.00	0.01	-0.07
THC	0.00	0.01	0.22	-0.12	0.34	0.04	0.07	-0.02	-0.07	-0.07
TRUST	-0.00	0.02	0.01	-0.10	0.01	0.02	-0.03	0.01	-0.07	-0.16
TX	0.03	0.06	0.04	-0.01	0.00	0.09	-0.02	0.00	-0.03	0.19
VIA	-0.01	0.00	0.06	-0.03	0.00	0.03	-0.04	0.07	-0.11	-0.03
VTR	-0.00	0.00	0.10	-0.13	-0.13	-0.13	0.04	-0.14	-0.11	-0.16
XDN	-0.00	-0.00	0.07	-0.04	-0.03	0.24	0.05	-0.07	-0.05	-0.05
XRP	0.00	0.01	0.02	-0.02	-0.02	-0.00	0.01	0.01	-0.17	-0.06
XST	0.00	0.05	0.12	-0.11	-0.06	0.01	-0.08	-0.01	-0.15	-0.24
XVG	0.06	0.01	0.07	-0.09	-0.05	0.56	-0.01	-0.03	0.14	0.04
XWC	-0.01	0.01	0.05	-0.06	-0.06	0.01	0.20	-0.16	-0.04	-0.06
Proportion of Explained Variance	0.14	0.09	0.06	0.05	0.04	0.04	0.03	0.03	0.02	0.02
Cumulative Explained Variance	0.14	0.24	0.30	0.35	0.39	0.43	0.46	0.48	0.51	0.53

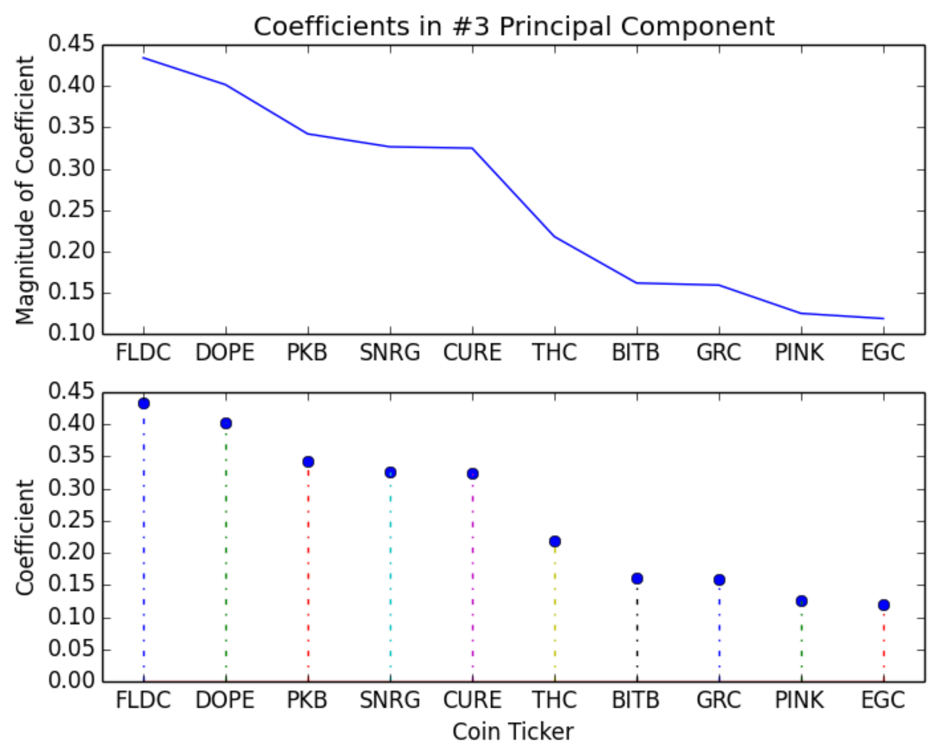
Coefficients for the top Crypto-Currencies by magnitude of coefficient for the first ten Principal Components.

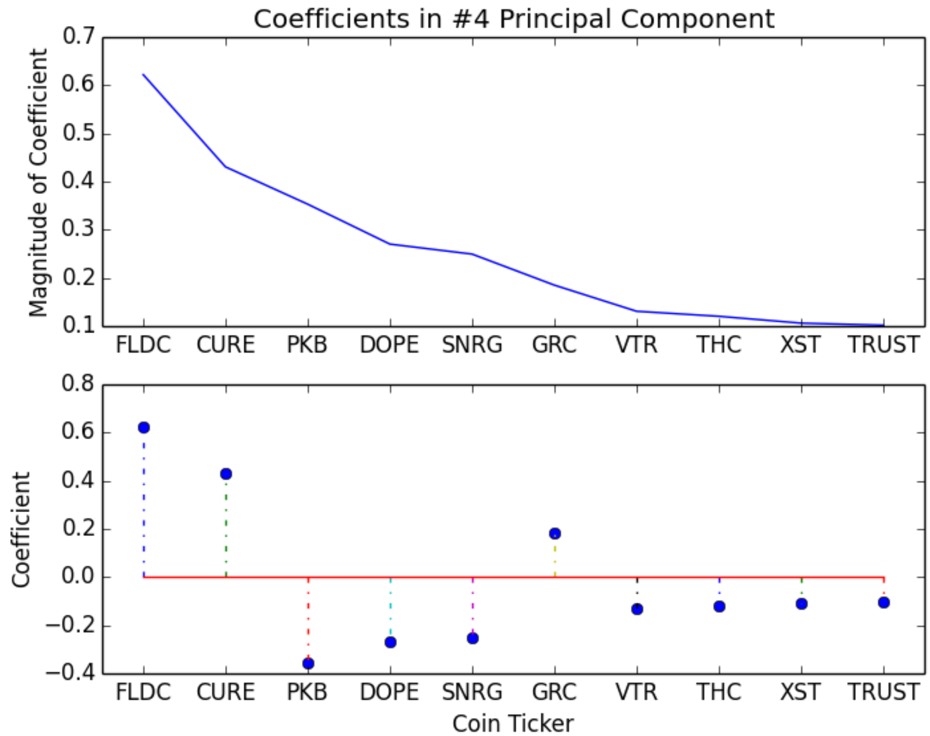
F Figures for the Principal Component Analysis

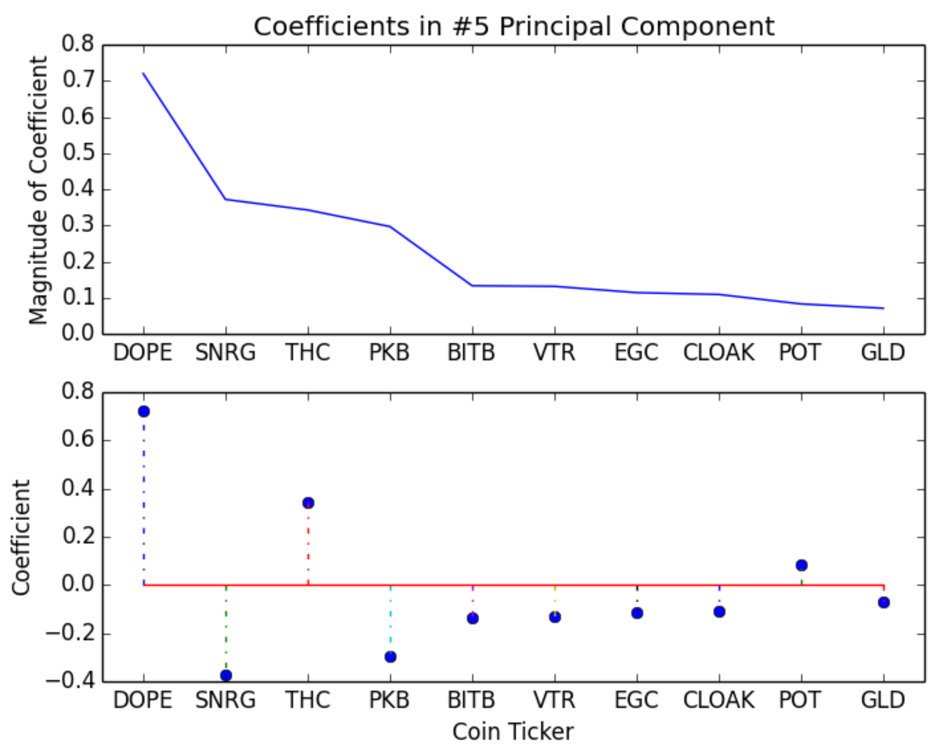





Coefficients in #2 Principal Component
Magnitude of Coefficient
1.0
0.8
0.6
0.4
0.2
0.0
EXCL PKB COVAL TX SLS XST NXT FLO SNRG POT
Coefficient
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
EXCL PKB COVAL TX SLS XST NXT FLO SNRG POT
Coin Ticker


Coefficients in #3 Principal Component
Magnitude of Coefficient
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
FLDC DOPE PKB SNRG CURE THC BITB GRC PINK EGC
Coefficient
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
FLDC DOPE PKB SNRG CURE THC BITB GRC PINK EGC
Coin Ticker


Coefficients in #4 Principal Component
Magnitude of Coefficient
FLDC CURE PKB DOPE SNRG GRC VTR THC XST TRUST
Coefficient
Coin Ticker


Coefficients in #5 Principal Component
Magnitude of Coefficient
DOPE SNRG THC PKB BITB VTR EGC CLOAK POT GLD
Coefficient
Coin Ticker

G Market Capitalization

Table 10: Market Capitalization of Crypto-Currencies in USD

Ticker	Name	June 26, 2016 Market Cap USD	(%) of Total Cyrpto Non-BTC Market Cap	June 26, 2017 Market Cap USD	(%) of Total Cyrpto Non-BTC Market Cap
ETH	Etherium	1160366285	55.92	29809370027	44.29
LTC	Litecoin	190272081	9.17	2434919043	3.62
DASH	Dash	44832114	2.16	1257842168	1.87
XMR	Monero	18790879	0.91	634302650	0.94
FCT	Factom	8998834	0.43	221777683	0.33
DCR	Decred	3375299	0.16	127318123	0.19
BTCD	BitCoinDark	1900818	0.09	83117691	0.12
PPC	Peercoin	9436815	0.45	75899599	0.11
XCP	Counterparty	4502941	0.22	45594270	0.07
OMNI	Omni	1092388	0.05	42015445	0.06
EXP	Expanse	537392	0.03	24619605	0.04
CLAM	Clams	1086834	0.05	14421401	0.02
SLS	SaluS	88023	0.00	12910604	0.02
NBT	NuBits	150216	0.01	228621	0.00
Cumulative		1445430919	69.66	34784336930	51.68
Total		2074877529	100	67302546296	100

The Name and Market Capitalization of Alt-Coin Market (Without Bicoin) in USD of top coins from PCA [8]. Sorted by June 25, 2017 Market Capitalization. Bitcoin went from a Capitalization of 83.24% to 37.68% over this period

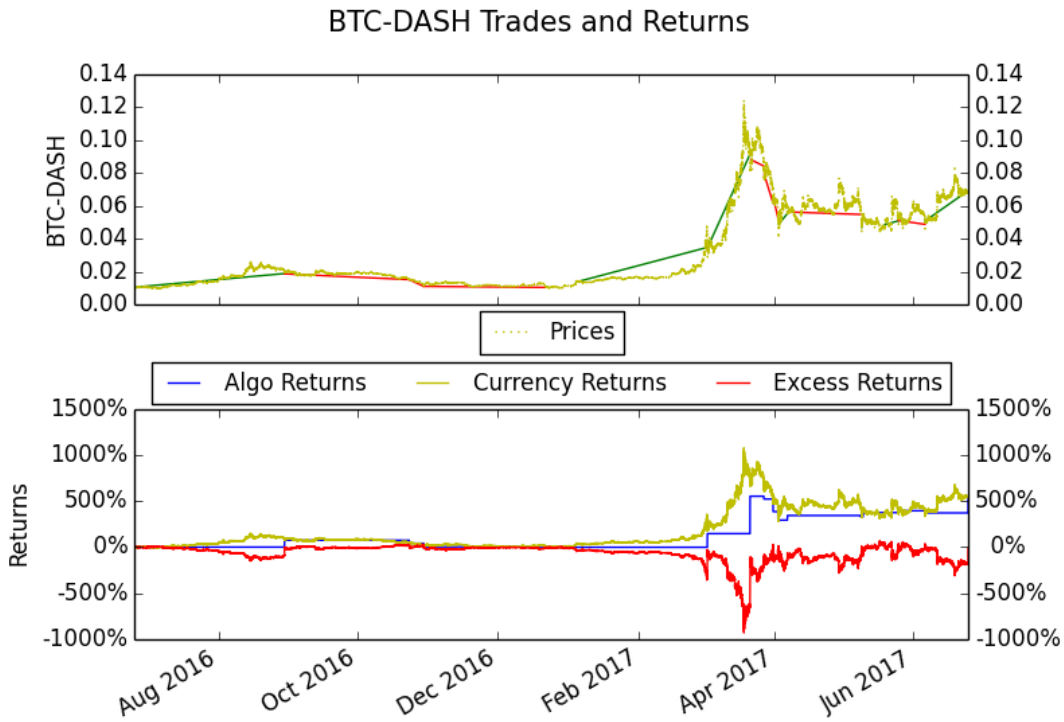
H Baseline Table

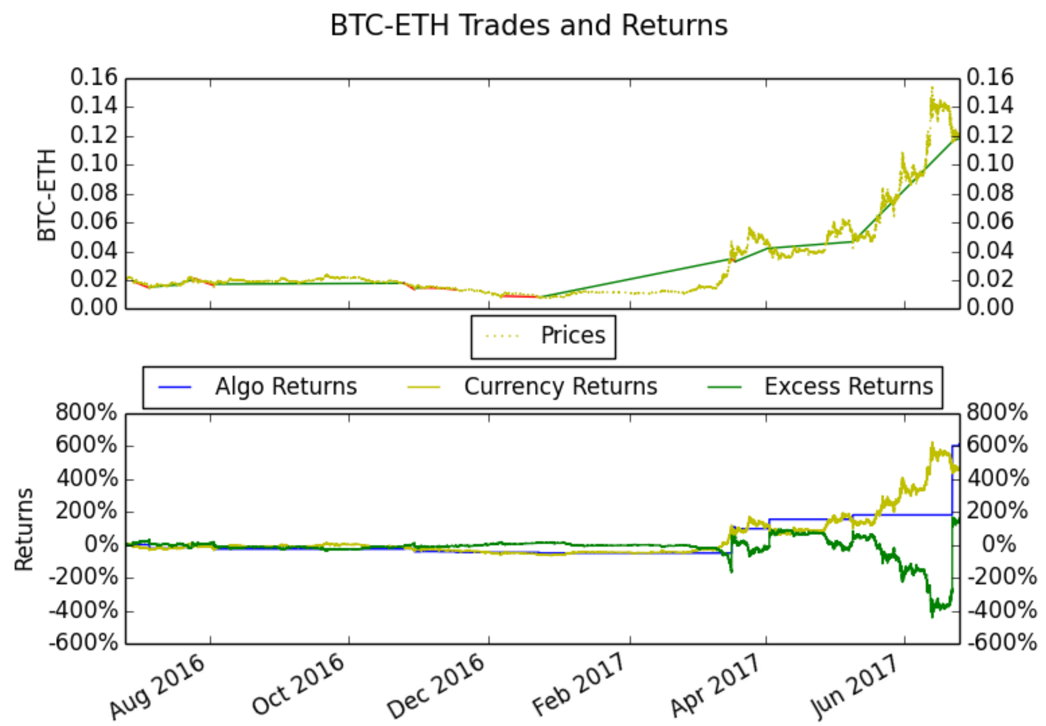
Table 11: Baseline Results of Holding Position from June 25, 2016 to June 25, 2017.

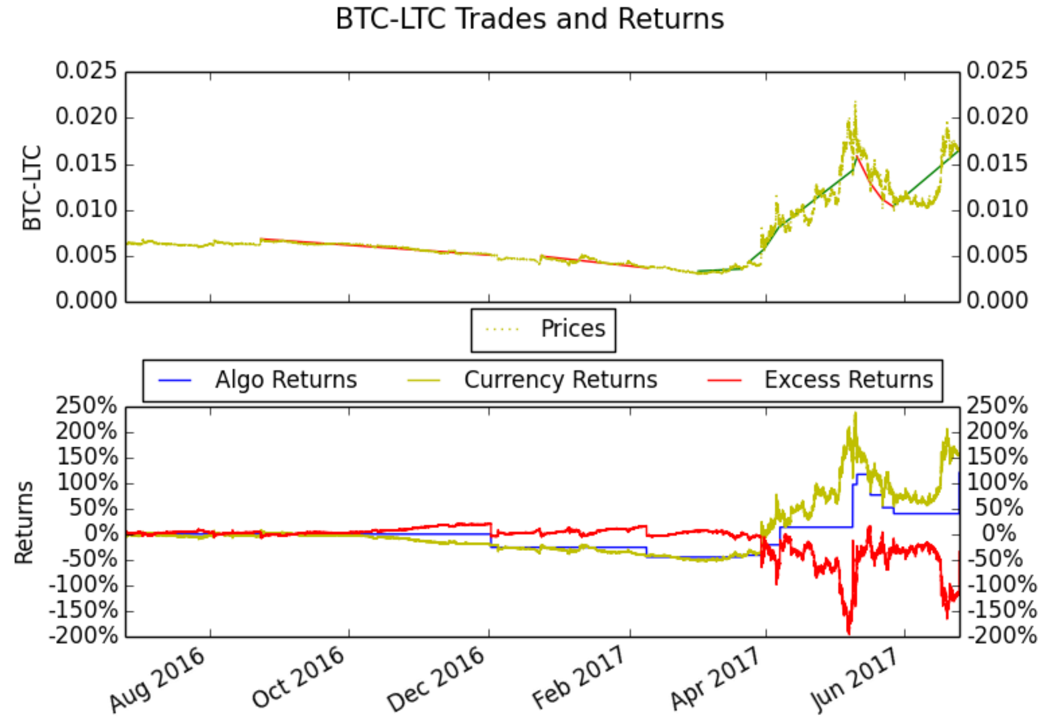
Market	Filter_Freq	Returns	No-cost Returns	Sharpe Ratio	Precision	Max Drawdown
BTC-ETH	1min	4.36	4.45	2.04	0.05	-0.70
BTC-ETH	5min	4.36	4.45	2.61	0.12	-0.94
BTC-ETH	15min	4.36	4.45	3.03	0.20	-0.82
BTC-ETH	30min	4.36	4.45	3.42	0.23	-0.79
BTC-ETH	1H	4.36	4.45	3.75	0.27	-0.78
BTC-ETH	6H	4.71	4.81	4.34	0.35	-0.71
BTC-ETH	12H	4.71	4.81	4.49	0.38	-0.72
BTC-ETH	24H	4.71	4.81	4.37	0.40	-0.69
BTC-XRP	1min	9.49	9.81	3.83	0.04	-0.76
BTC-XRP	5min	9.49	9.81	4.13	0.10	-1.00
BTC-XRP	15min	9.50	9.82	4.51	0.17	-1.00
BTC-XRP	30min	9.50	9.82	4.94	0.22	-0.99
BTC-XRP	1H	9.50	9.82	5.16	0.29	-0.93
BTC-XRP	6H	9.77	10.10	6.01	0.37	-0.76
BTC-XRP	12H	9.77	10.10	6.22	0.37	-0.73
BTC-XRP	24H	9.77	10.10	5.86	0.39	-0.70
BTC-LTC	1min	1.62	1.64	0.86	0.03	-0.57
BTC-LTC	5min	1.62	1.64	1.02	0.09	-1.00
BTC-LTC	15min	1.62	1.64	1.15	0.16	-0.79
BTC-LTC	30min	1.62	1.64	1.24	0.21	-0.75
BTC-LTC	1H	1.62	1.64	1.37	0.25	-0.64
BTC-LTC	6H	1.51	1.53	1.46	0.30	-0.61
BTC-LTC	12H	1.51	1.53	1.51	0.31	-0.59
BTC-LTC	24H	1.51	1.53	1.46	0.33	-0.58
BTC-DASH	1min	4.89	5.00	1.79	0.04	-0.68
BTC-DASH	5min	4.89	5.00	2.18	0.13	-1.00
BTC-DASH	15min	4.93	5.03	2.61	0.22	-0.99
BTC-DASH	30min	4.93	5.03	3.01	0.28	-0.89
BTC-DASH	1H	4.93	5.03	3.38	0.32	-0.76
BTC-DASH	6H	5.01	5.12	4.08	0.41	-0.61
BTC-DASH	12H	5.01	5.12	4.25	0.41	-0.60
BTC-DASH	24H	5.01	5.12	4.57	0.45	-0.58
BTC-XMR	1min	6.39	6.55	2.35	0.03	-0.77
BTC-XMR	5min	6.39	6.55	2.60	0.12	-1.00
BTC-XMR	15min	6.39	6.55	3.01	0.21	-1.00
BTC-XMR	30min	6.39	6.55	3.35	0.26	-0.97
BTC-XMR	1H	6.39	6.55	3.63	0.31	-0.88
BTC-XMR	6H	6.51	6.68	4.28	0.39	-0.75
BTC-XMR	12H	6.51	6.68	4.56	0.42	-0.74
BTC-XMR	24H	6.51	6.68	5.00	0.45	-0.74

Data Point Frequency is referred to by Filter_Freq. The Annualized Sharpe Ratio changes with data point frequency due to the annualizing multiplier.

I Walk-Forward Momentum Plots






BTC-LTC Trades and Returns
BTC-LTC
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0.020
0.015
0.010
0.005
0.000
Prices
Algo Returns
Currency Returns
Excess Returns
Returns
250%
200%
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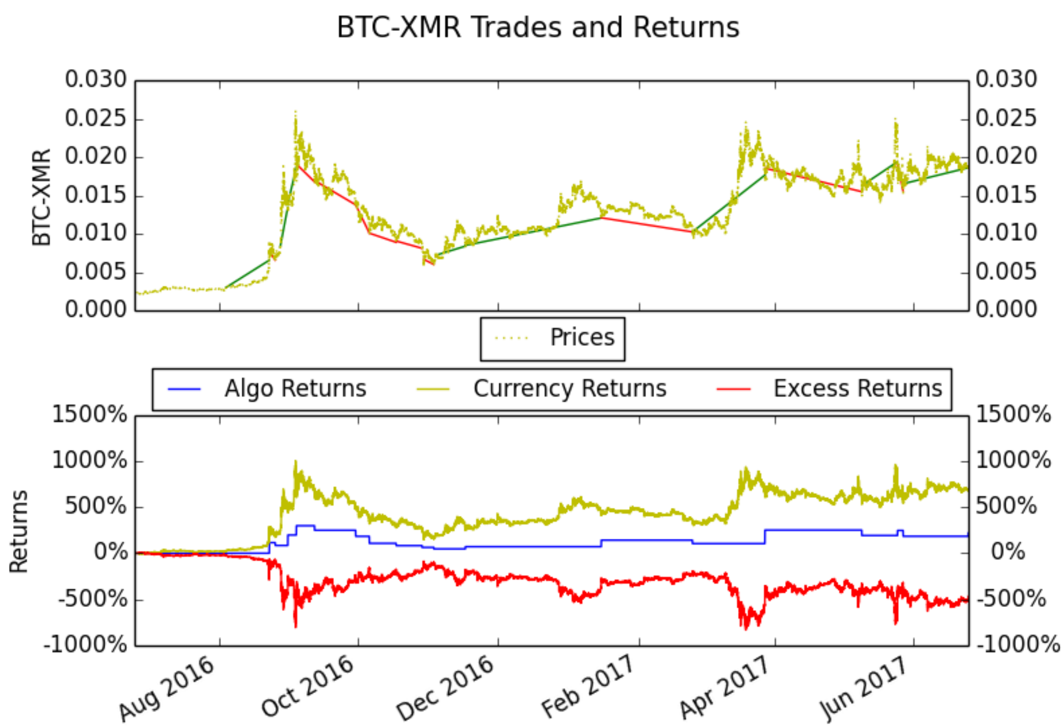
Dec 2016
Feb 2017
Apr 2017
Jun 2017


BTC-XMR Trades and Returns
BTC-XMR
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0.025
0.020
0.015
0.010
0.005
0.000
Prices
Algo Returns
Currency Returns
Excess Returns
Returns
1500%
1000%
500%
0%
-500%
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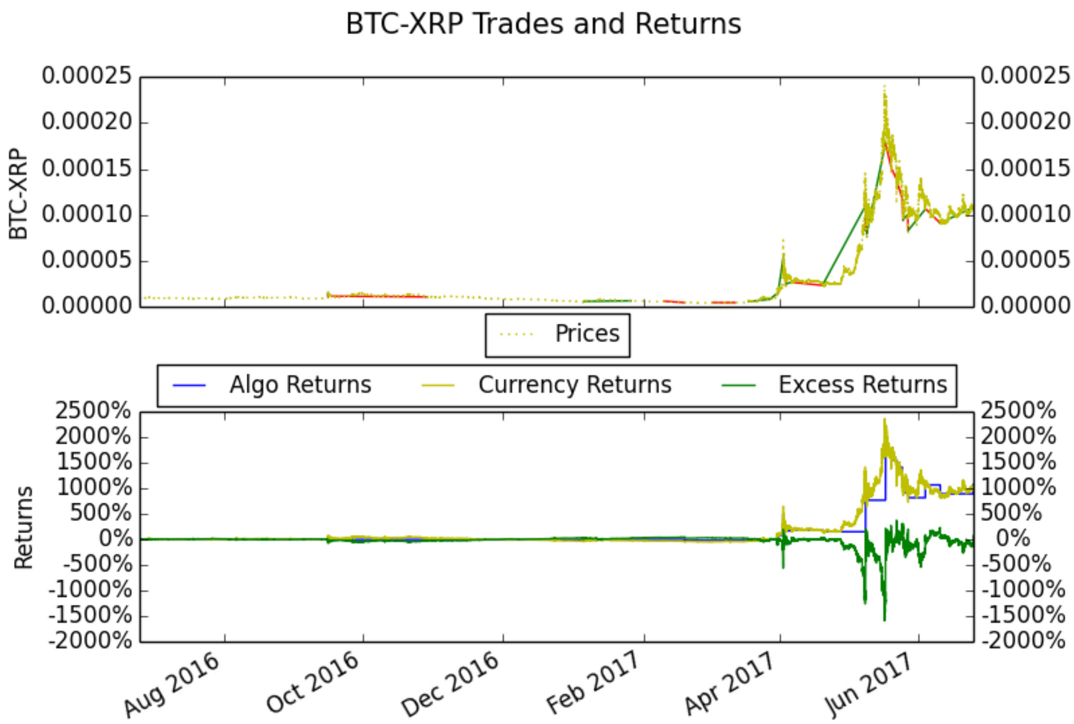
Dec 2016
Feb 2017
Apr 2017
Jun 2017


BTC-XRP Trades and Returns
BTC-XRP
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0.00020
0.00015
0.00010
0.00005
0.00000
Prices
Algo Returns
Currency Returns
Excess Returns
Returns
2500%
2000%
1500%
1000%
500%
0%
-500%
-1000%
-1500%
-2000%
Aug 2016
Oct 2016
Dec 2016
Feb 2017
Apr 2017
Jun 2017

J Statistical Arbitrage Results

Table 12: Statistical Arbitrage Strategy Results from June 25, 2016 to June 25, 2017.

Pair	Filter Freq	Returns	Sharpe Ratio	Max Drawdown	Transaction Count	No-cost Returns
ETH,XRP	6H	0.13	1.17e-01	-0.74	48	0.29
ETH,XRP	12H	0.49	5.56e-01	-0.54	25	0.59
ETH,XRP	24H	0.23	3.46e-01	-0.36	10	0.27
ETH,LTC	6H	-0.17	-3.04e-01	-0.78	53	-0.05
ETH,LTC	12H	-0.30	-4.80e-01	-0.75	24	-0.26
ETH,LTC	24H	0.05	7.04e-02	-0.48	13	0.09
ETH,XMR	6H	-0.02	-4.47e-02	-0.78	52	0.12
ETH,XMR	12H	0.44	7.29e-01	-0.58	23	0.53
ETH,XMR	24H	0.02	3.85e-03	-0.74	11	0.05
LTC,XRP	6H	0.60	6.78e-01	-0.59	60	0.86
LTC,XRP	12H	0.88	8.70e-01	-0.61	23	1.00
LTC,XRP	24H	0.58	7.60e-01	-0.47	10	0.62
LTC,XMR	6H	-0.23	-3.72e-01	-0.87	52	-0.12
LTC,XMR	12H	0.02	1.40e-02	-0.50	24	0.09
LTC,XMR	24H	0.97	1.11e+00	-0.66	10	1.02
DASH,ETH	6H	0.37	3.84e-01	-0.58	45	0.54
DASH,ETH	12H	0.50	7.39e-01	-0.44	20	0.60
DASH,ETH	24H	0.52	6.62e-01	-0.56	13	0.57
DASH,XRP	6H	-0.42	-4.44e-01	-0.90	50	-0.35
DASH,XRP	12H	0.11	9.97e-02	-0.65	22	0.17
DASH,XRP	24H	0.15	1.94e-01	-0.54	10	0.18
DASH,LTC	6H	0.22	2.31e-01	-0.63	48	0.40
DASH,LTC	12H	-0.14	-2.14e-01	-0.69	23	-0.09
DASH,LTC	24H	0.63	8.05e-01	-0.61	13	0.69
DASH,XMR	6H	0.05	4.29e-02	-0.66	50	0.21
DASH,XMR	12H	0.09	1.21e-01	-0.59	22	0.16
DASH,XMR	24H	-0.22	-3.01e-01	-0.71	14	-0.20
XMR,XRP	6H	-0.34	-3.96e-01	-0.81	51	-0.25
XMR,XRP	12H	0.24	2.68e-01	-0.62	25	0.33
XMR,XRP	24H	0.56	7.18e-01	-0.57	8	0.60

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