# *The crypto-exposure strategy*

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## *STRATEGY SPECIFICATION*

### *Introduction*

This strategy is designed to exploit crypto-market inefficiencies through statistical analysis of market data. The objective of the strategy is to generate risk-adjusted alpha through a systematic approach to trading that involves identifying and exploiting short-term price differences between highly correlated crypto-securities.

### *Investment Universe*

The strategy will focus on liquid and highly correlated securities traded on major crypto exchanges such as Binance. The securities will be selected based on their market capitalization[1]. For the purpose of this strategy, we choose BTC, and ETH.[2]

[1] This data is fetched from coinmarketcap.com

[2] BTC - Bitcoin, ETH - Ethereum

### *Algorithms and Models*

The strategy will utilize a combination of statistical models, including co-integration, mean reversion, and regression analysis, to identify opportunities for profitable trades. The models will be constantly updated to account for changes in market conditions and market trends.

### *Data Sources*

The strategy will use historical daily closing price data to inform its trading decisions. Data sources are: CoinMarketCap, and Yahoo Finance.

### *Risk Management*

The strategy will be managed in accordance with strict risk management policies and guidelines. This will include monitoring the strategy's performance and exposure to market risk, and adjusting the trading algorithms as needed to ensure that risk is managed within acceptable levels. Risk metrics such as volatility, downside risk, maximum drawdown will be regularly monitored to inform profit taking and risk stops.

## *Constraints and Limitations*

The strategy will be subject to constraints, including limitations on the maximum drawdown a trade is allowed to take. The strategy may also be subject to liquidity constraints, which may limit the ability to enter or exit positions in a timely manner.

## *Conclusion*

The crypto-exposure strategy is a systematic approach to trading that is designed to exploit market inefficiencies in the crypto-universe through the use of statistical models.

# *STRATEGY BACKTEST REPORT*

## *INTRODUCTION*

In the crypto-space, it is generally true that the price movements of Bitcoin (BTC) have a significant impact on the rest of the cryptocurrency market. Bitcoin is the largest and most well-established cryptocurrency by market capitalization. Its price movements often set the tone for the rest of the market and have been known to trigger wider price swings in other cryptocurrencies. This is due in part to the fact that many investors and traders consider Bitcoin to be the *"gold standard"* of cryptocurrencies, and its price performance can influence their buying and selling decisions for other digital assets. The correlations[3] with other coins can occur for a variety of reasons, such as differences in market sentiment, trading volumes, or underlying use cases.

[3] Both positive and negative

Most crypto-currencies are positively correlated with Bitcoin (BTC), such as Ethereum (ETH, the second largest coin by market capitalization), and others. However, some cryptocurrencies have been known to exhibit a negative correlation with Bitcoin and they include: Decentralized StableCoin (DAI).

It's important to note, however, that correlations between cryptocurrencies can change over time and may not always remain consistent. Additionally, correlations can be affected by various factors, such as regulatory developments, market conditions, and global economic events, among others. As a result, it's crucial to monitor the relationship between cryptocurrencies and to regularly reassess their correlations in order to make informed investment decisions.

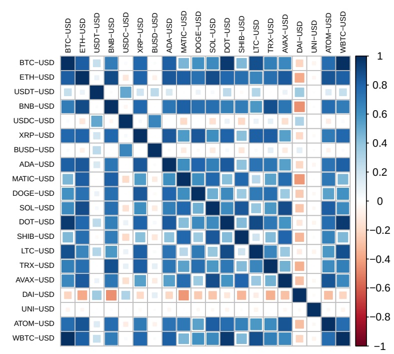


Figure 1: Price correlation

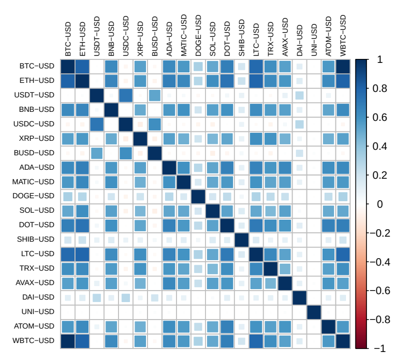


Figure 2: Returns correlation

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For crypto traders and anyone seeking exposure to the crypto-space, this presents an opportunity to take advantage of these relationships by executing trades between assets to potentially profit from price discrepancies. One such relationship that has been observed is between Bitcoin (BTC) and Ethereum (ETH), where they are said to have a cointegrating relationship.

In this strategy, we aim to actively trade ETH by exploiting this relationship and capturing any relative price movements between the two assets. The goal is to generate returns through short-term exposure to the crypto-assets while managing downside risk effectively.

## Objectives, Constraints, Benchmark

### Objective

The strategy objective is to gain exposure in crypto subject to minimum acceptable return, drawdown and downside risk constraints.

To achieve this, the portfolio is constructed to take advantage of the co-integration existing between the two largest crypto assets: BTC and ETH. So that, in the event BTC moves in a certain direction, and ETH lags in following the said direction, then we bet that, it is soon going to follow in the same direction and we act accordingly.

For instance:

- If BTC makes a down turn, and ETH lags behind, then we bet that ETH is bound to make a down turn as well, and thus we ensure our portfolio positions are in line with that i.e. we minimize our ETH holdings.[4]

[4] Sell high

- If BTC makes an up turn, and ETH lags behind, then we bet that ETH is bound to make an up turn as well, and thus we ensure our portfolio positions are in line with that i.e. we maximize our ETH holdings.[5]

[5] Buy low

### Constraints

The following are the constraints for this strategy:

- Minimum acceptable return: 15% Annualized Return.
- Drawdown constraints: 30% Maximum Drawdown

### Benchmarks

Since we are solely trading ETH, a good benchmark is a buy-hold portfolio of ETH, BTC, and an equally weighted portfolio of ETH and BTC. The benchmarks are chosen in this manner, since majority of crypto traders trade ETH and BTC for the most part - as they are the most liquid crypto-currencies.

### Indicator

For this trading strategy, we rely on the strong linear relationship between BTC and ETH, and thus we use a rolling OLS regression model to capture the said relationship The residuals(from now on called: spread) series emerging from the model, will be the indicator for the trading strategy.

In testing the indicator, we expect the spread series to exhibit a short half life, exhibit a high speed of reversion to mean, exhibit zero mean, and stationarity as measured by the Augmented Dickey-Fuller test.

### *Signal*

The signals for this trading strategy are generated as a result of the interaction between the spread series, and a threshold chosen. The threshold is a parameter to be optimized and ranges between -0.5 to 0.5.

In the case that, the spread series exceeds the chosen threshold, then it implies that ETH is Over-valued, and in the case the spread series is below the chosen threshold, then it implies that ETH is Under-valued.

### *Filter*

For the purpose of backtesting this strategy, a walk-forward analysis is implemented. Parameters which perform best in-sample are used for Out-of-Sample testing, and the rest are discarded.

### *Rules*

The trading rules follow from the signals as shown below:

We EXIT any LONG positions we have on ETH, when ETH is over-valued, and we ENTER into a LONG position on ETH in the case ETH is under-valued.

$$S_t > Threshold := ETH \;\; Over \;\; valued \;\;\; := SELL \;\; ETH$$

$$S_t <= Threshold := ETH \;\; Under \;\; valued \;\;\; := BUY \;\; ETH$$

*Results*

We implement a walk-forward analysis to backtest the strategy, where we use two years as an optimization period, and one year as the validation period. This gives a total of 4 iterations over our dataset containing 1922 days of price data

The in-sample spread statistics are shown below:

| Period | Mean | Reversion speed | Half life | Variance | Chosen threshold |
|---|---|---|---|---|---|
| 2017-11-09::2019-10-29 | -1.45 | 0.00 | 404.27 | 0.01 | -0.4 |
| 2018-11-03::2020-10-23 | 0.15 | 0.01 | 94.05 | 0.02 | -0.1 |
| 2019-10-29::2021-10-18 | 0.16 | 0.01 | 78.17 | 0.02 | 0.5 |
| 2020-10-23::2022-10-13 | 0.59 | 0.00 | 150.86 | 0.01 | 0.5 |

The out-of-sample spread statistics are shown below:

| Period | Mean | Reversion speed | Half life | Variance | Threshold used |
|---|---|---|---|---|---|
| 2019-10-29::2020-10-23 | 0.73 | 0.01 | 86.92 | 0.01 | -0.4 |
| 2020-10-23::2021-10-18 | 1.10 | 0.01 | 115.65 | 0.01 | -0.1 |
| 2021-10-18::2022-10-13 | 0.57 | 0.02 | 37.70 | 0.02 | 0.5 |
| 2022-10-13::2023-02-12 | 0.03 | 0.05 | 15.28 | 0.09 | 0.5 |

The above tables show the distributions for the long-term mean, variance, half life, and speed of reversion, as well as optimal thresholds picked for both the in sample and out-of-sample periods. It is notable that the mean reverts around a value of 0, as does the threshold.

Past the 2nd optimization set[6], the volatility rises, which is accompanied by a higher speed of reversion and a lower half life, implying that for trading mean-reversion strategies, a higher volatility for the spread series, or indicator in use is useful.

[6] The 3rd optimization set covers the dates: 2021-10-18::2022-10-13 and the 4th optimization set covers the dates: 2022-10-13::2023-02-12. These two optimization phases intersect at the year 2021, which was marked by a recovering and highly volatile crypto market.

The spread series is shown below, for the validation phases combined:


The overall spread series for the validation sets combined is highly mean reverting with a half-life of 32 days, long term mean of -0.01178704, and volatility of 20.85%. These statistics strongly favor our strategy, which belongs to the class of mean-reversion strategies.[7]

[7] The blue horizontal line indicates the evolution of the threshold across the validation phases.

The trade statistics for the four validation runs is shown below:

| | Set: 1 | Set: 2 | Set: 3 | Set: 4 |
|---|---|---|---|---|
| Number of Trades | 10.00 | 5.00 | 8.00 | 10.00 |
| Net Trading P/L | 7831.60 | 121980.74 | -56012.30 | -7794.82 |
| Average Trading P/L | 940.87 | 25038.00 | -5945.03 | 681.72 |
| Largest Winner | 9228.52 | 44610.80 | 11149.05 | 4516.46 |
| Largest Loser | -1180.08 | -3834.42 | -23879.33 | -4186.48 |
| Gross Profits | 13132.42 | 129024.40 | 15508.55 | 14680.94 |
| Gross Losses | -3723.71 | -3834.42 | -63068.81 | -7863.75 |
| Winning Trades(%) | 40.00 | 80.00 | 50.00 | 80.00 |
| Losing Trades (%) | 60.00 | 20.00 | 50.00 | 20.00 |
| Average Daily P/L | 940.87 | 25038.00 | -5945.03 | 681.72 |
| MaxDrawdown | -3431.94 | -23085.44 | -113656.07 | -15466.51 |
| Profit-to-MaxDrawdown | 2.28 | 5.28 | -0.49 | -0.50 |

The strategy's worse period was 2021-10-18::2022-10-13, as shown by the drawdown statistic, while the strategy's best period was during 2020-10-23::2021-10-18 (the most volatile period). The average number of trades as shown is roughly 8 trades.[8]

[8] I implement a 1% transaction cost per trade (both opening and closing positions.)

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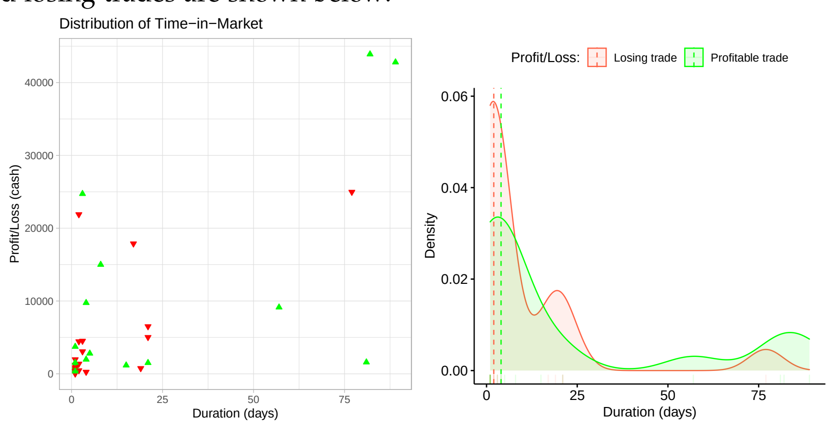
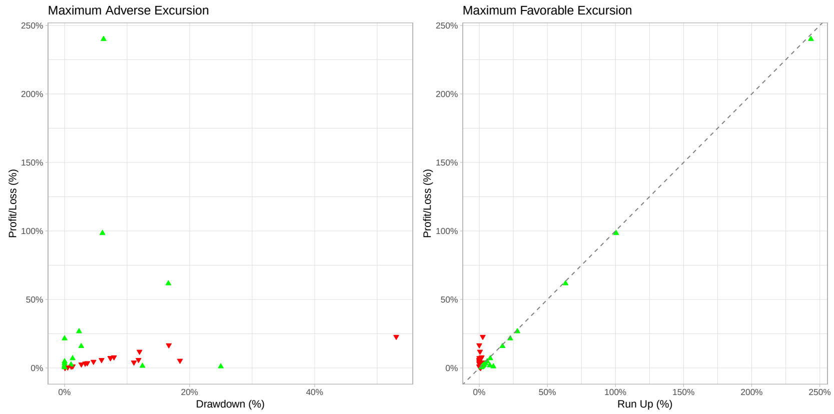
The strategy's distribution of time in market for both the profiting and losing trades are shown below:




There is a big overlap between the time-in-market for both the profitable and losing trades, with majority trades having longer active durations being profitable. This overlap confirms the difficulty of setting an exit barrier based on duration in market.

A chart for the Maximum Favorable and Adverse Excursion is shown below:[9]

[9] The green triangles denote profitable trades, while the red inverted triangles denote losing trades.




From the MAE plot below, a stop loss set at 17% is optimal, since it shuts two losing trades, and one winning trade (although the winning trades gives a net trading profit of below 2%). For the MFE, the alignment of the trades makes it a tough choice to set a take profit level, hence we do not use take profits for this strategy.[10]

[10] Maximum Favorable Excursion (MFE) is the highest potential profit a trade earns before it is closed, while Maximum Adverse Excursion (MAE), is the largest drawdown a trade experiences before it is closed. The MFE guides in setting an optimal take profit, while the MAE guides in setting an optimal stop losses.

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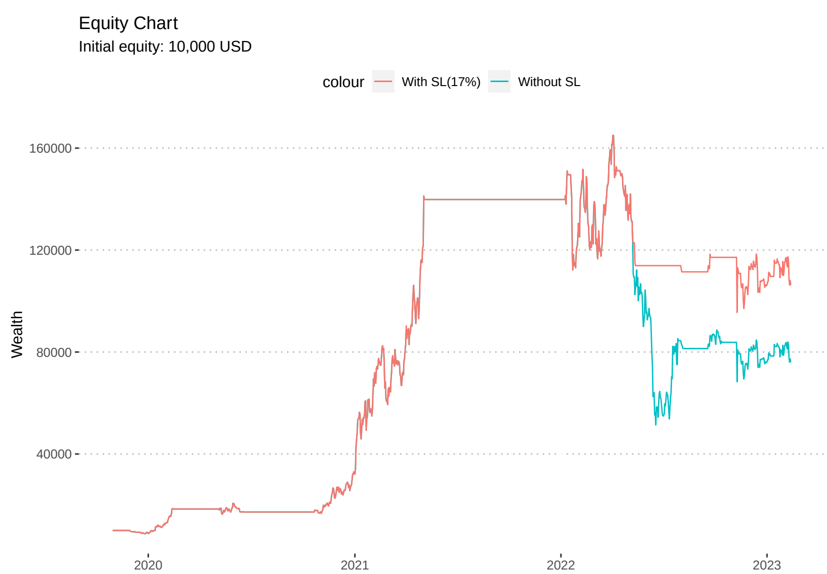


| | Without SL | With SL(17%) | ETH(BH) | BTC(BH) | BTC−ETH(EQW) |
|---|---|---|---|---|---|
| *Annualized Return* | 53.0% | 64.1% | 55.5% | 19.8% | 41.7% |
| *Annualized Volatility* | 52.0% | 45.9% | 77.7% | 58.6% | 69.3% |
| *Annualized Sharpe(Rf=0%)* | 1.0189 | 1.3972 | 0.7136 | 0.3378 | 0.6022 |
| *Maximum Drawdown* | 68.9% | 42.1% | 79.4% | 76.6% | 77.7% |
| *End Equity* | 76005.22 | 106253.77 | 82030.21 | 23668.1 | 52757.09 |

The equity curves, and portfolio return summaries are shown above for the strategy (with and without the risk stop), as well as the benchmarks. The benchmarks are not plotted in the equity comparison curve to avoid cluttering.[11]

[11] ETH(BH) ans BTC(BH) represents a Buy-Hold portfolio in ETH(BTC) for the period under consideration, while BTC-ETH(EQW) represents a portfolio comprising of both ETH and BTC in equal weights.

The strategy benchmark statistics are shown:[12]

| | ETH(BH) | BTC(BH) | BTC-ETH(EQW) |
|---|---|---|---|
| Alpha | 0.0014 | 0.0019 | 0.0015 |
| Beta | 0.3439 | 0.3563 | 0.3675 |
| Beta+ | 0.4253 | 0.3154 | 0.4415 |
| Beta- | 0.2070 | 0.2943 | 0.2290 |
| R-squared | 0.3392 | 0.2069 | 0.3077 |
| Annualized Alpha | 0.4066 | 0.6036 | 0.4629 |
| Correlation | 0.5824 | 0.4549 | 0.5547 |
| Correlation p-value | 0.0000 | 0.0000 | 0.0000 |
| Tracking Error | 0.6318 | 0.5562 | 0.5812 |
| Active Premium | 0.0867 | 0.4433 | 0.2241 |
| Information Ratio | 0.1372 | 0.7970 | 0.3855 |
| Treynor Ratio | 1.8645 | 1.7999 | 1.7448 |

The strategy indeed over-performs the benchmarks, with minimal tracking error, and little correlation (below 55%) for almost all benchmarks.

[12] These statistics are generated relative to the strategy's return. Beta+(-) implies Beta during bull(bear) markets.

## *Conclusion*

From the backtest report, it is evident that the strategy delivers good performance over the years, and especially in highly volatile market regimes. For profitable trading however, risk stops have to be put in place, to ensure that downside risk is limited, as has been shown by how effective the 17% stop loss rule has improved the strategy.

The strategy surpasses its minimum acceptable return, but exceeds the drawdown limit imposed by 12%.

The out-of-sample results indicate that the strategy placed only 35 trades over a period of 1203 days, which might be small for conducting meaningful post-trade analysis. More trades need to be observed, in order to have robust estimates of post trade analysis.

## *Recommendations*

The walk forward analysis assumes a ratio of 2:1 for the in-sample and out-of-sample set sizes. Other combinations such as 3:1 need to be tested, as it can be shown to drastically change the strategy's performance.

Using BTC daily prices as the dependent variable in the model assumes that movements in the price of ETH are solely explained using BTC price movements. Other variables could be explored such as: using crypto-currency ETFs, or utilizing other crypto currency datasets, using techniques for modelling high dimensional data[13]

[13] see: Learning representations in High Dimensional Data

*References*

Peterson, B. G. (2015). Developing & backtesting systematic trading strategies. *DV Trading*. http://goo.gl/na4u5d