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Token Inflation Study

Relationship of Token Inflation and Return

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Research and Insights

Data Report

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Contents

1. Executive Summary

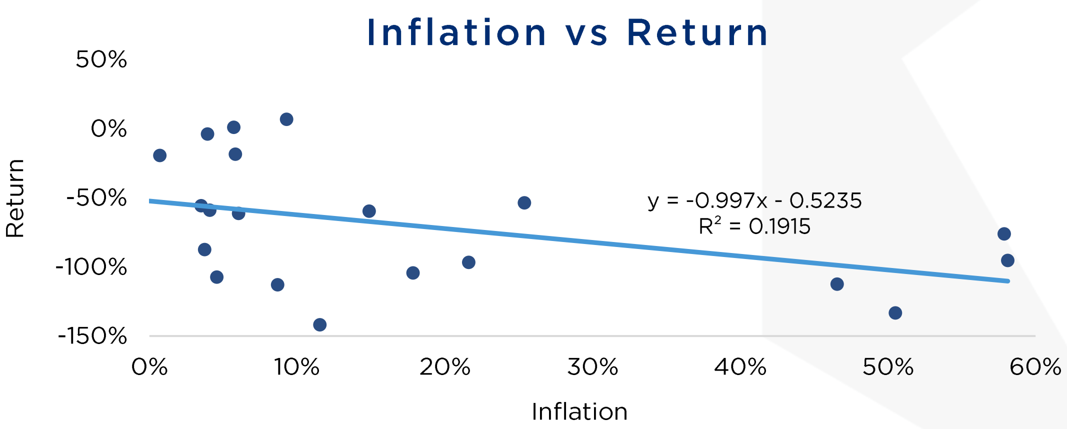
Other things being constant, it is reasonable to assume that the higher the token inflation, the worse the price performance of a token. In order to verify the statement, we proposed to investigate the relationship between token inflation and return. In addition, we are also interested to discover the relationship between token inflation and change of market capitalization.

Here is a quick take away for those in a hurry:

- There exists the weak negative linear relationship between inflation and return. The higher the inflation, the lower the return
- There is no relationship between inflation and market cap change
- We cannot accept the alternative hypothesis that "low inflation tokens have better return than high inflation tokens". This means that we don't have a statistically strong evidence to support the first statement

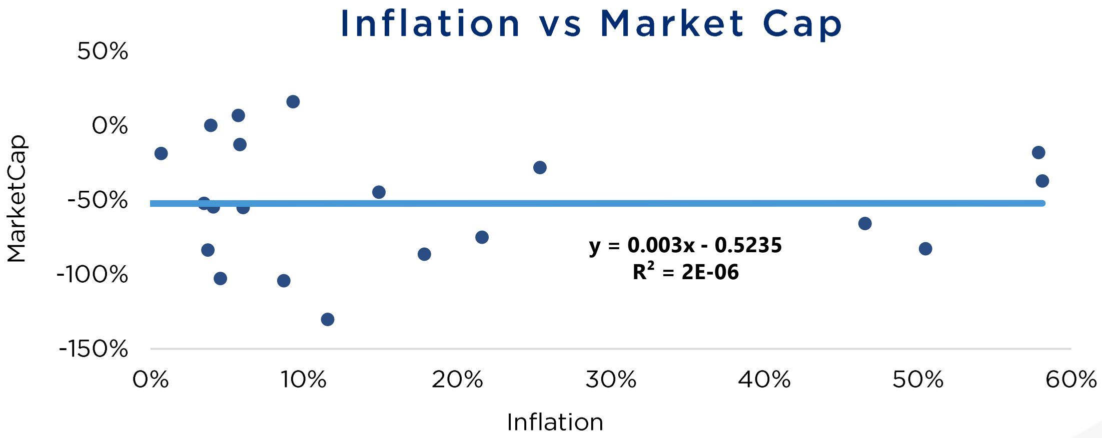
Result indicates a negative relationship between inflation and return:

- Correlation: -0.44
- Regression Slope: -0.997
- R^2: 0.1915



While there is no relationship between inflation and market cap:

- Correlation: 0.00
- Regression Slope: 0.003
- R^2: 0.000002



We have further performed a hypothesis test on checking the average returns of high inflation tokens versus low inflation tokens.

$$H_0: \mu_{low} = \mu_{high}$$
$$H_1: \mu_{low} > \mu_{high}$$

The p-value of the one tailed t-test is 0.251, indicating we cannot accept the alternative hypothesis. i.e. It is NOT statistically significant to tell that "low inflation tokens have better return than high inflation tokens".

2. Introduction

The purpose of this document is to:

- Provide a methodology to analyse the relationship between tokens' inflation and their return or market capitalization change

Cryptocurrency market has more than 2,000 tokens as of today. Some tokens have lower inflation but some tokens have high inflation depending on their supply schedule. Other things being constant, it is reasonable to assume that the higher the token inflation, the worse the return of a token in the long run.

$$Market\ Cap = Price \times Supply$$

To test if the above statement is true, we have used the 3 methods below:

- Linear regression
- Pearson correlation
- Hypothesis test

In addition, we are also interested to discover the relationship between inflation and market capitalization change rate. Normally we may assume market cap to be constant, but one cannot rule out the possibility that inflation has an impact on market cap as well.

3. Methodology

3.1 Data and Data Extraction

To avoid selection bias, we have randomly selected 20 (+1) from the TOP 200 tokens in terms of market capitalization (The #0 is bitcoin). The tokens' information is from the CoinMarketCap on 25/11/2019 as shown below:

Seq	Rank	Logo	Name	Abbreviation
0	1		Bitcoin	BTC
1	3		Ripple	XRP
2	5		Bitcoin Cash	BCH
3	18		NEO	NEO
4	20		IOTA	MIOTA
5	23		Dash	DASH
6	39		0x	ZRX
7	55		Komodo	KMD
8	66		Siacion	SC
9	74		Verge	XVG
10	86		Horizen	ZEN
11	90		Steem	STEEM
12	104		Zcoin	XZC
13	116		Tierion	TNT
14	123		Factom	FCT
15	142		Loopring	LRC
16	152		FunFair	FUN
17	162		Dentacoin	DCN
18	178		Metal	MTL
19	181		Groestlcoin	GRS
20	198		Vertcoin	VTC

The following data for each token is extracted:

- Date: the date of the historical data
- Close: the close price of the token
- Market Cap: the market capitalization

Token price and market cap data are downloaded and processed in Microsoft excel. Some data cleansing and reformatting is performed to make dataset suitable for further calculation.

3.2 Return

2-year return is chosen in this project, and the designated period is from 22/11/2017 to 21/11/2019. Return is calculated with the formula:

$$Return = ln\left(\frac{Price_{2019}}{Price_{2017}}\right) * \frac{365}{730}$$

where 730 is the duration from 22/11/2017 to 21/11/2019 and 365 in the numerator is to annualize it (i.e., annualized continuous return).

Natural log is used for measuring continuous compounding rate:

$$Price_T = Price_{T-1} * e^{\mu}$$

Take the Bitcoin Cash (BCH) for example, the return is calculated as:

Date	Close Price	Return
22/11/2017	1303.31	-
21/11/2019	226.6	-87.59%

The above methodology aligns with the Geometric Brownian Motion (GBM) which is widely used to model stock return:

$$dS = \mu Sdt + \sigma SdZ_t$$

where $dZ_t \sim N(0, t)$, and therefore

$$ln\left({}^{S_t}/_{S_{t-1}}\right) = \mu dt + \sigma dZ$$

which implies that $ln\left({}^{S_t}/_{S_{t-1}}\right) \sim N(\mu - \frac{\sigma^2}{2}, \sigma^2)$

3.3 Token Supply and Inflation

Before calculating inflation, we need to know each coin's total supply for the period. As we know that:

$$Market\ Cap\ =\ Price\ \times\ Supply$$

Token supply can be estimated by:

$$Supply \approx \frac{Market\ Cap}{Close\ Price}$$

Therefore annual inflation can be estimated by:

$$Annual\ Inflation\ = \ln\left(\frac{Supply_{2019}}{Supply_{2017}}\right) * \frac{365}{730}$$

Take the Bitcoin Cash (BCH) for example, the annual inflation is calculated as:

Date	Close Price	Market Cap	Token Supply	Inflation
22/11/2017	1303.31	21,917,585,065	16,816,862.50	–
21/11/2019	226.6	4,107,271,775	18,125,647.73	3.75%

3.4 Market Capitalization

Resemble the return calculation above, the market cap change of a single token is simply calculated by replacing the supply in the formula above to "Market Cap".

Take the Bitcoin Cash (BCH) for example, the market cap change is calculated as:

Date	Market Cap	Market Cap Change
22/11/2017	4,107 million	–
21/11/2019	21,917 million	-83.73%

3.5 Pearson Correlation Coefficient

The correlation coefficient is a statistical measure that calculates the strength of the relationship between the relative movements of two variables. The value ranges between -1.0 and 1.0. A correlation of -1.0 shows a perfect negative correlation, while a correlation of 1.0 shows a perfect positive correlation. A correlation of 0.0 shows no relationship between the movement of the two variables.

The best-known and most commonly used type of correlation coefficient is the Pearson product-moment correlation coefficient. It is a measure of the strength and direction of the linear relationship between two variables that is defined as the covariance of the variables divided by the product of their standard deviations. The expression of Pearson correlation coefficient is:

$$\rho_{xy} = \frac{Cov(x,y)}{\sigma_x \sigma_y}$$

, where

- ρ_{xy} = Pearson product-moment correlation coefficient
- $Cov(x,y)$ = covariance of variables x and y
- σ_i = standard deviation of variable i (i = x, y)

In this project, we use the Pearson correlation coefficient to estimate the linear relationship between inflation and return and the linear relationship between inflation and market cap change. We set

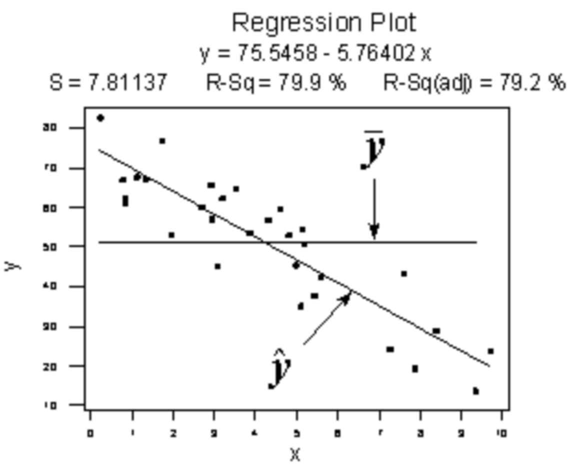
- x = {all tokens' inflation}
- y = {all token's return},

then the ρ_{xy} is the Pearson correlation coefficient between inflations and returns.

3.6 R-Squared (R^2)

R-squared (R^2) is a statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables in a regression model. It explains to what extent the variance of one variable explains the variance of the second variable. Since R^2 is a proportion, it is always a number between 0 and 1.

If R^2 = 1, all of the data points fall perfectly on the regression line. The predictor x accounts for all the variation in y. If R^2 = 0, the estimated regression line is perfectly horizontal. The predictor x accounts for none of the variation in y. Let's look at an example to illustrate this (The Coefficient of Determination, R^2):



$$SSR = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2 = 6679.3$$

$$SSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 = 1708.5$$

$$SSTO = \sum_{i=1}^{n}(y_i - \bar{y})^2 = 8487.8$$

$$R^2 = \frac{SSR}{SSTO} = 1 - \frac{SSE}{SSTO}$$

In this report, we use R^2 to measure how much prediction error we eliminated via our linear regression model. In other words, R^2 is used to assess our linear regression.

3.7 Hypothesis Test

Although the regression shows a potential negative relation between inflation and return, the R^2 is too small to make any conclusion. To further verify our findings, we introduce hypothesis test.

In hypothesis test, tokens are divided into two groups: high inflation and low inflation. The high / low inflation is defined by:

$$Category = \begin{cases} High\ (if\ Annual\ Inflation\ \geq\ 20\%) \\ Low\ (if\ Annual\ Inflation\ <\ 20\%) \end{cases}$$

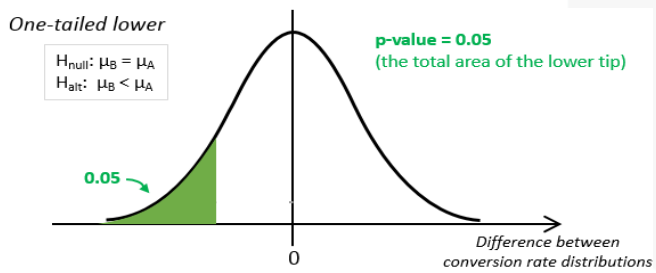
We set the null hypothesis (H_0): the average return of tokens in low inflation group equals to the average return of tokens in high inflation group; the alternative hypothesis (H_1): the average return of tokens in low inflation group is greater than that of high inflation group. The null and alternative hypothesis can be illustrated below:

$$H_0: \mu_{low} = \mu_{high}$$
$$H_1: \mu_{low} > \mu_{high}$$

We then conduct a two-sample (unpaired) one-tailed t-test. The test-statistics can be calculated by:

$$T = \frac{\hat{\mu}_{low} - \hat{\mu}_{high}}{\sqrt{s_{low}^2/N_{low} + s_{high}^2/N_{high}}}$$

The test statistics will then be fitted into a t-distribution with degree of freedom equals $N_{low} + N_{high} - 2$. This will give us the p-value for the hypothesis test.



We will accept the alternative hypothesis if the p-value is smaller than 0.05. Otherwise, we reject the alternative hypothesis and accept the null hypothesis. In our case, $\mu_{low} = \mu_{high}$.

4. Result and Analysis

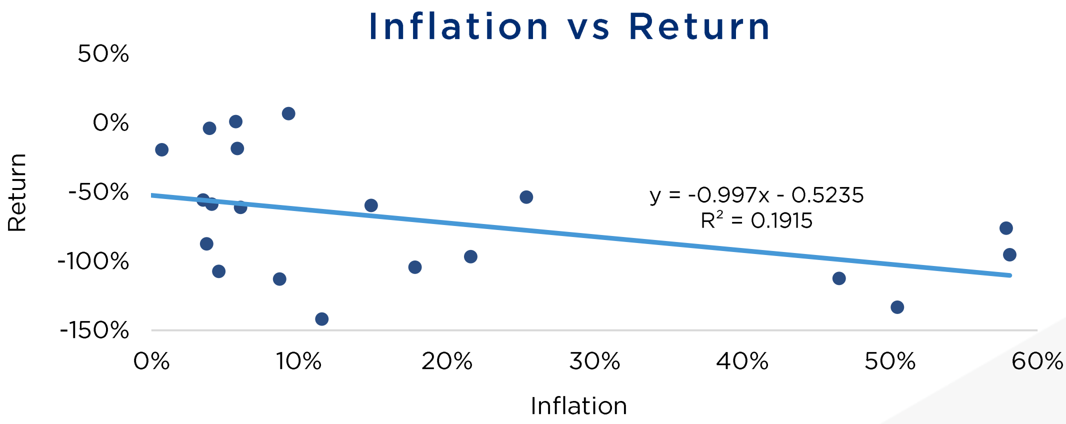
4.1 Basic Statistics

The basic statistic for all tokens is summarized in the table below:

Seq	Rank	Logo	Name	Abbreviation	Inflation	Return	△MarketCap
0	1		Bitcoin	BTC	4.01%	-3.85%	0.08%
1	3		Ripple	XRP	5.89%	1.02%	6.74%
2	5		Bitcoin Cash	BCH	3.82%	-87.59%	-83.84%
3	18		NEO	NEO	4.18%	-58.90%	-54.80%
4	20		IOTA	MIOTA	0.00%	-68.82%	-68.82%
5	23		Dash	DASH	9.08%	-113.04%	-104.35%
6	39		0x	ZRX	9.75%	6.78%	16.08%
7	55		Komodo	KMD	6.24%	-61.22%	-55.17%
8	66		Siacion	SC	16.08%	-59.71%	-44.80%
9	74		Verge	XVG	6.01%	-18.50%	-12.67%
10	86		Horizen	ZEN	78.54%	-76.20%	-18.24%
11	90		Steem	STEEM	19.58%	-104.36%	-86.48%
12	104		Zcoin	XZC	59.40%	-112.50%	-65.88%
13	116		Tierion	TNT	0.70%	-19.40%	-18.70%
14	123		Factom	FCT	4.67%	-107.46%	-102.89%
15	142		Loopring	LRC	78.96%	-95.39%	-37.19%
16	152		FunFair	FUN	24.16%	-96.78%	-75.14%
17	162		Dentacoin	DCN	28.95%	-53.71%	-28.28%
18	178		Metal	MTL	65.82%	-133.39%	-82.82%
19	181		Groestlcoin	GRS	3.57%	-55.75%	-52.25%
20	198		Vertcoin	VTC	12.27%	-142.05%	-130.48%

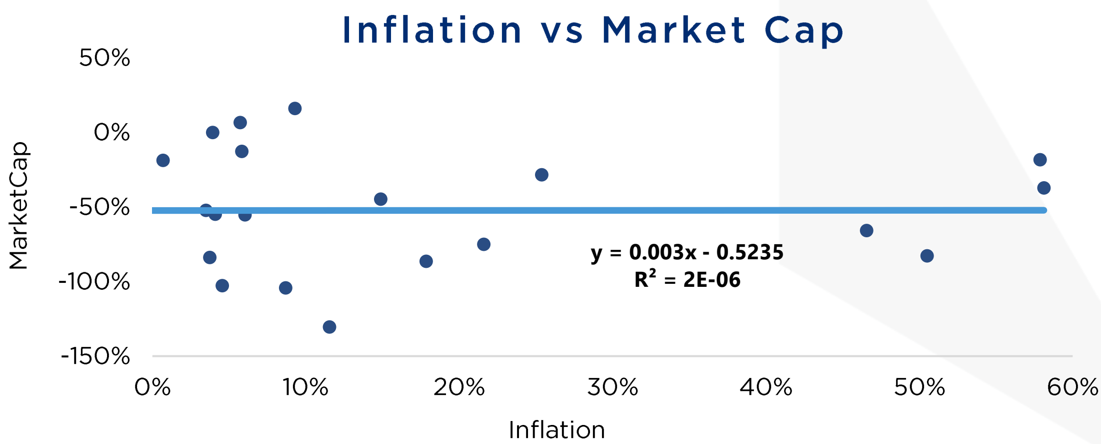
4.2 Inflation vs Return

The relationship between inflation and return is plotted below. Regression shows a lower return when inflation increase (**Slope** = -0.997). The correlation coefficient is **-0.44**, indicating a negative linear relationship. The R^2 is **0.1915:** the regression model has weak ability to explain inflation against return.



4.3 Inflation vs Market Cap Change

The relationship between inflation and market cap change is plotted below. The regression line is almost flat (**Slope** = **0.003**). The correlation coefficient is **0.00**, indicating no linear relationship. The R^2 (**0.000002**) is almost zero: the regression doesn't help to explain the relation between inflation and market cap.



4.4 Hypothesis Test

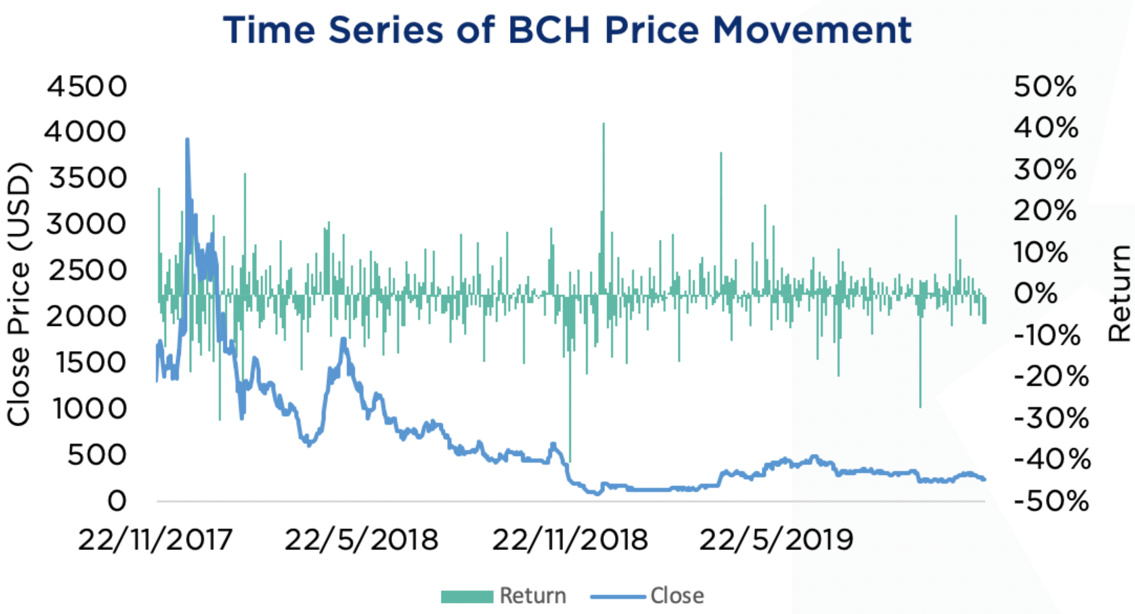
By using the classification methods mentioned in last section, tokens are either classified as "High Inflation" or "Low Inflation":

Category	Tokens
High Inflation	{XZC, FUN, MTL, ZEN, LRC, DCN}
Low Inflation	{BTC, BCH, MIOTA, ZRX, XVG, STEEM, TNT, VTC, XRP, NEO, DASH, KMD, SC, FCT, GRS}

Assuming the return in line with a Geometric Brownian Motion (GBM), we calculate the daily return for each token:

$$r_t^{token} = ln\left({}^{S_t}/_{S_{t-1}}\right)$$

Using BCH as example, the time series of the price movement can be illustrated as below:



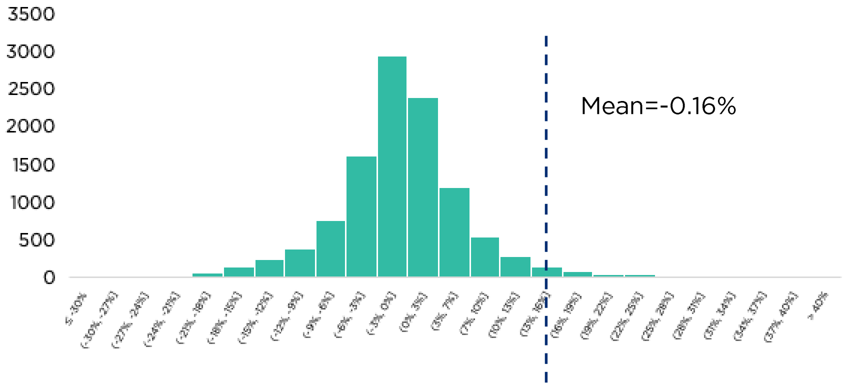
As discussed, we have set the null and alternative hypothesis:

$$H_0: \mu_{low} = \mu_{high}$$
$$H_1: \mu_{low} > \mu_{high}$$

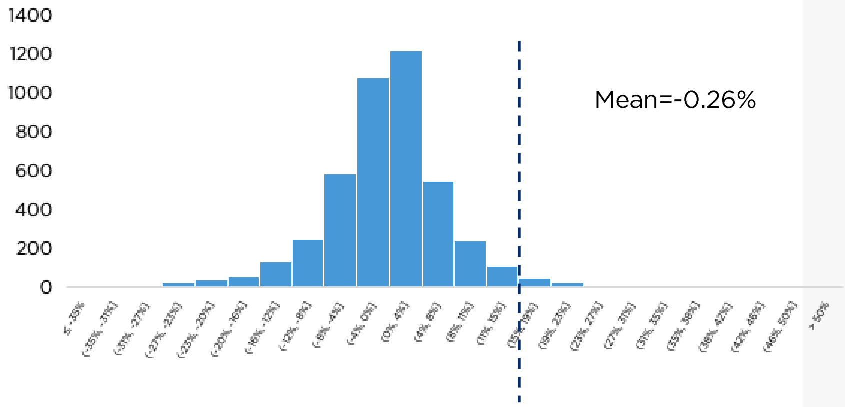
The p-value of the one tailed t-test Is **0.251**, indicating we **cannot reject** the null hypothesis. i.e. It is **NOT** statistically significant to tell that the average return of high inflation tokens is lower than that of the low inflation tokens.

The histograms for those daily returns are:

Histogram of Return for Low Inflation Tokens



Histogram of Return for High Inflation Tokens



Inflation	Average	Stdev	Count	p-value
Low	-0.16%	7.29%	10,935	0.251
High	-0.26%	8.29%	4,374	

5. Summary

5.1 Conclusion

From above results, we can have the following conclusions:

- There exists the weak negative linear relationship between inflation and return. The higher the inflation, the lower the return
- There is no relationship between inflation and market cap change
- We cannot accept the alternative hypothesis that "low inflation tokens have better return than high inflation tokens". This means that we don't have a statistically strong evidence to support the first statement

5.2 Limitations and Caveats

Although we have concluded the results as above, we would still like to highlight some limitations and further improvements that can be performed for the study:

- 20 sample tokens are likely not enough. We may further increase the number tokens
- Using different study time frames may yield different results. We are currently arbitrarily picking 2 years and started at 22/11/2017
- High inflation is defined by "20%", which is subjective
- Price are measured in USD. We can consider measuring in BTC
- Return may not follow a normal distribution

6. Reference

CoinMarketCap. (2019, Nov 25). Retrieved from CoinMarketCap: https://coinmarketcap.com/

Dmouj, A. (2006, November). *Stock price modelling: Theory and Practice*.

Correlation Coefficient. (n.d.). Retrieved from https://www.investopedia.com/terms/c/correlationcoefficient.asp

The Coefficient of Determination, R^2. (n.d.). Retrieved from STAT 501: Regression Methods: https://online.stat.psu.edu/stat501/lesson/1/1.5/1.5.2

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