

## **Correlations of Cryptocurrencies Time Series**

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#### 1.) Introduction

#### **Cryptocurrency Background**

Cryptocurrencies have been gained much attention from media and academic alike for its volatility and skyrocketed price since 2<sup>nd</sup> quarter of 2017. Cryptocurrencies are digital assets designed to act as medium of exchange using the latest advances from blockchain technology, cryptography and decentralized protocols.

According to Goldman's Head of Global Investment Research, Steve Strogin, the high market correlations between prices of cryptocurrencies seem to act like a single asset class. The purpose of this project is to investigate the correlations between prices of cryptocurencies, namely Bitcoin (XBT/BTC), Ethereum (ETH) and Litecoin (LTC).

### **Computational Background**

Cross-correlation between two signals u(t) and v(t) can be mathematically represented as follow. For continuous function v(t) & u(t), we have  $\int_{-\infty}^{\infty} u^*(\tau-t)\,v(\tau)\,d\tau$  . For discrete functions v(t) & u(t), we then have  $\sum_{k=-\infty}^{\infty} u^*(\tau-t)v(\tau) d\tau$ .

Autocorrelation is correlation within a dataset and can indicate a trend. It is a mathematical representation of the correlation of a given time series and a lagged version of itself over successive time intervals. It can be mathematically represented as follow  $R(s,t) = \frac{E[x_t - u_t]E[x_s - u_s]}{\sigma_t \sigma_s}$ 

$$R(s,t) = \frac{E[x_t - u_t]E[x_s - u_s]}{\sigma_t \sigma_s}$$

If autocorrelation is positive, it indicates that the error of signal tends to have the same sign as it moves over time. Negative correlation usually occurs when positive error term is followed by negative error, then followed by positive and so on.

In summary, cross-correlation is used to find when two different signals are similar. Autocorrelation is is used to observe whether error terms in a regression are correlated.



### 2.) Problems and Questions

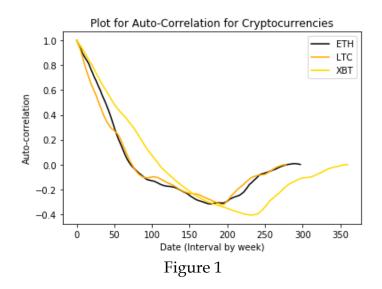
The market data for this project is obtained through quandl.com, a market place for financial, economic or alternative data for analysis. The prices of cryptocurrencies are procured from different cryptocurrencies exchanges, namely GDAX and Coinbase, to reflect market averages from Feb 2<sup>nd</sup> 2017 to April 4<sup>th</sup> 2018.

To determine the correlation between the cryptocurrencies, the methods of cross-correlation and autocorrelation are used for analysis. To note, the goal of the project is to show that there is high correlation between the cryptocurrencies such that it behaves like a single asset class and possibly obtain some insights from its price history. Error indicates price fluctuation.

### 3.) Analysis and Results

#### i.) Autocorrelation

#### Results:



#### **Analysis:**

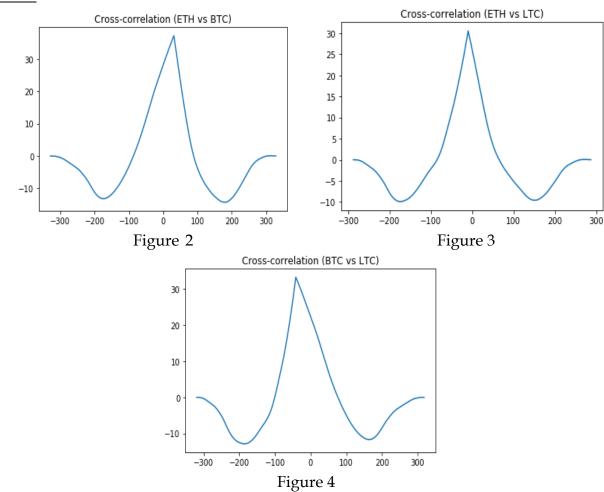
In the first 75 days, the autocorrelations are positive, well above 0.5. This indicates the prices of cryptocurrencies had been steady for quite a while, often in increasing trend. However, from 100<sup>th</sup> day onwards, as they slowly descended to the negative zone, prices of each cryptocurrencies experienced a lot of volatility. These observations can be corroborated with the prices history in appendix.

There is likely a strong correlation among three cryptocurrencies because they have almost the similar decreasing/increasing trends and shapes. This indicates the price of cryptocurrencies tend to behave similarly to each other.



#### ii.) Cross-correlation

#### Results



#### <u>Analysis</u>

In Figure 2, it peaks around at 39 when the time lag,  $\tau$  = 25 and remains above 50% of the peak value for lags up to approximately 75 days. This indicates that bitcoin price is likely to have high correlation with Ethereum price.

In Figure 3, it peaks at 30 when time lag,  $\tau$  = 25 and remains above 50% of the peak value up to merely 25 days. However, it can be seen that Ethereum is likely to have higher correlation with Bitcoin than Litecoin.

Finally in Figure 4, the peak value of 32 occurs when time lag  $\tau$  is around 0 (slightly shifted to negative  $\tau$ ) and remained above 55% of the peak value for approximately 50 days. This also shows that correlation between Bitcoin and Litecoin is not as high as that of Bitcoin and Ethereum. This is more likely to happen because, in general, market capitalization of Ethereum is second to that of Bitcoin.



### 4.) Discussions

Cross-correlation shows that there is a higher correlation between prices of Bitcoin and Ethereum. Nonetheless, autocorrelation has shown that the prices of cryptocurrencies are more likely to be correlated to each other. Exchange occasionally reflects higher or lower prices than market averages; hence, it is good practice to pull more data from different exchanges too. There are plenty of cryptocurrencies that show strong correlation with digital gold, "Bitcoin". This would allow other weaker correlated cryptocurrencies to be analysed in their own domains for traders' advantage.

To apply more broadly, several other indicators such as oscillators, Pearson Correlation Matrix and risk profiles could be used to gain insights about the momentum of the prices. Many factors such as number of transactions, trading volume and number of users could be considered to show stronger market correlations. Interesting insights can also be gained by analysing the frequency of media posts, and number of Google searches.

### 5.) Conclusion

Given its high volatility, analyzing the market correlations of cryptocurrencies allow us to understand the prices of cryptocurrency. In this project, cryptocurrencies are more likely to behave like a single asset class due to their strong correlations. This constitutes considerable opportunities to analyse further for digital assets trading.

### 6.) References

- 1.) Nakamoto, Satoshi. Bitcoin: A Peer-to-Peer Electronic Cash System. 2008.
- 2.) A. Yaffe, Robert. An Introduction to Time Series Analysis and Forecasting. 1999
- 3.) Nishizawa,Kana. Get Ready for Most Cryptocurrencies to Hit Zero, Goldman Says. Feb 6<sup>th</sup>, 2018.



# Appendix

The plots below show the prices of cryptocurrencies from Feb  $20^{th}$  2017 to April  $4^{th}$  2018.

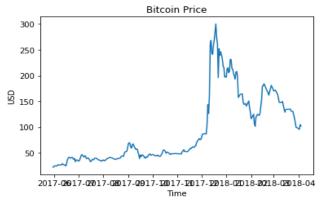


Figure 5

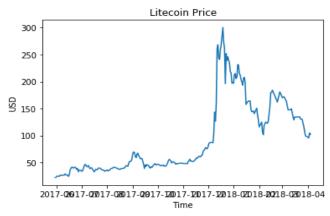


Figure 6

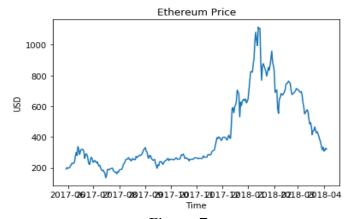


Figure 7



#### **Codes**

Below is the code snippet for this project.

```
1. import os, quandl, pickle
import numpy as np
import pandas as pd
4. import matplotlib.pyplot as plt
5.
6.
7. # download data from Quandl website
8. def data_arrays(ID):
9.
        try:
            data = open('{}.pkl'.format(ID).replace('/','-'), 'rb')
10.
11.
            df = pickle.load(data)
12.
        except (OSError, IOError) as e:
13.
            df = quandl.get(ID, returns="pandas")
14.
            df.to_pickle(data)
15.
        return df
16.
17. # function for autocorrelation
18. def AC(x):
19. x = np.array(x)
        arr = x - sum(x)/(len(x))
20.
        auto = np.correlate(arr, arr, mode = 'full')
21.
22.
        auto = auto[len(auto)//2:]
23.
        auto /= auto[::-1][-1]
24.
        return auto
25.
26. btc = data_arrays('BCHARTS/COINBASEUSD')
27. eth = data_arrays('GDAX/ETH_EUR')
28. ltc = data_arrays('GDAX/LTC_EUR')
29.
30. # Creating an average value form high and low
31. ltc['Mean'] = (ltc['High']+ltc['Low'])*(1/2)
32. eth['Mean'] = (eth['High']+eth['Low'])*(1/2)
33. btc['Mean'] = (btc['High']+btc['Low'])*(1/2)
34.
35. # Setting up dates
36. eth = eth['2017-2-20':'2018-4-4']
37. ltc = ltc['2017-2-20':'2018-4-4']
38. btc = btc['2017-2-20':'2018-4-4']
39.
40. # Calculate autocorrelation and transform result to Pandas Dataframe
41. eth = AC(eth['Mean'])
42. \#eth = eth/max(eth)
43.
44. btc = AC(btc['Mean'])
45. #btc = btc/max(btc)
46.
47. ltc = AC(ltc['Mean'])
48. #ltc = ltc/max(ltc)
49.
50. #eth_vs_btc = np.correlate(eth,btc,'full')
51. #num = len(eth_vs_btc)
52. #t = np.arange(-num/2,num/2)
53. #plt.plot(t, eth_vs_btc)
54. #plt.title("Cross-correlation (ETH vs BTC)")
```



```
55.
56. #eth_vs_ltc = np.correlate(eth,ltc,'full')
57. #num = len(eth_vs_ltc)
58. #t = np.arange(-num/2, num/2)
59. #plt.plot(t, eth_vs_ltc)
60. #plt.title("Cross-correlation (ETH vs LTC)")
61.
62. #btc vs ltc = np.correlate(btc,ltc,'full')
63. #num = len(btc_vs_ltc)
64. \#t = np.arange(-num/2,num/2)
65. #plt.plot(t, btc_vs_ltc)
66. #plt.title("Cross-correlation (BTC vs LTC)")
67.
68. #plt.plot(btc)
69. #plt.title("Bitcoin Price")
70. #plt.ylabel("USD")
71. #plt.xlabel("Time")
72.
73. #plt.plot(ltc)
74. #plt.title("Litecoin Price")
75. #plt.ylabel("USD")
76. #plt.xlabel("Time")
77.
78. #plt.plot(eth)
79. #plt.title("Ethereum Price")
80. #plt.ylabel("USD")
81. #plt.xlabel("Time")
82.
83. #plt.plot(eth, color= "black")
84. #plt.plot(ltc, color = "orange")
85. #plt.plot(btc, color ="gold") #normalized coefficient for cross correlation
86. ##plt.title("Plot for Auto-correlation for Litecoin") # Bitcoin, Ethereum too
87. #plt.title("Plot for Cross-Correlation for Litecoin") # Bitcoin, Ethereum too
88. #plt.ylabel("Auto-correlation")
89. #plt.xlabel("Date (Interval by week)")
90. #plt.legend(['ETH','LTC','XBT'],loc='upper right')
91. #plt.show()
```