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Causal dependencies on the crypto market employing techniques of Network Science

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1 Introduction

This project aims to discover and confirm the causal dependencies of the crypto market. To achieve this goal I've gathered historical data on the crypto market price from the beginning of 2021 (current year) to June. I've then fitted an Autoregressive Model (VAR) and analysed the result.

2 Cryptocurrency market

Seven crypto have been chosen due to their importance in nowadays market. These coins are:

- Bitcoin (BTC)
- Ethereum (ETH)
- Uniswap (UNI)
- Cardano (ADA)
- Binance coin (BNB)
- Pancakeswap (CAKE)
- Monero (XMR)

Historically, Bitcoin was the first cryptocurrency to ever being developed and since then it dominated the cryptocurrencies market. As Fig. 1 shows, Bitcoin dominates the market with roughly 80% of the market capitalization. Bitcoin high value is mainly given by two reasons:

1. It's the most known and "trusted" cryptocurrency.
2. It has a limited supply.

This makes Bitcoin a perfect store of value asset. This also makes people laud Bitcoin as the "digital gold". However, Bitcoin blockchain technology is outdated making it unusable from a practical point of view. The transactions are slow and inherent with high fees. Moreover, with the rise of altcoins [1]and in particular Ethereum, Bitcoin is losing its central role in the cryptocurrencies market as shown in Fig. 1 dropping only recently from 80% market capitalization to 60% (which is still huge though). Due to its high market capitalization, Bitcoin "dictates" the price of other cryptocurrencies. When Bitcoin rises, all the altcoins rise. When Bitcoin falls, all the altcoins fall. In short, Ethereum and Bitcoin are the "big players" in the market.

[1]Alctoin means *alternative coin* with respect to Bitcoin

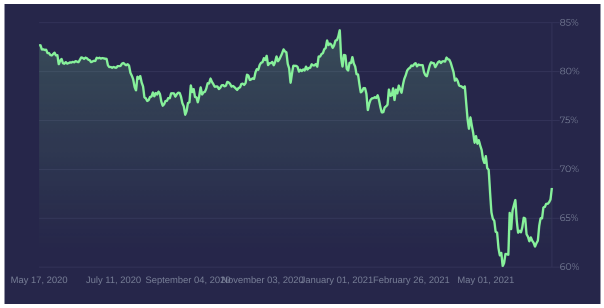


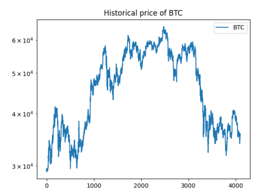
Figure 1: Bitcoin historically dominance over the market.
Image gently taken from `https://bitcoindominance.com/`

A special comment needs to be made on Uniswap (UNI) and Pancakeswap(CAKE). These projects are Decentralized Finance (De-Fi) and allow a user to ”swap” two cryptos without an intermediate i.e. the exchange. In particular, UNI is built over ETH and CAKE over the BNB blockchain.

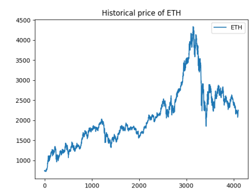
3 Preliminary analysis

The crypto historical market data for the 7 coins can be seen in Fig. 2. At first look, it’s clear that all the markets have some similarity in the behaviour: bullish markets with a recent dip in the price. In particular, CAKE seems to follow the price trend of BNB pretty closely. This is, as explained in Sec. 2 makes sense since CAKE is built on top of BNB. The same should technically be true for UNI and ETH, however, that pattern is less visible.

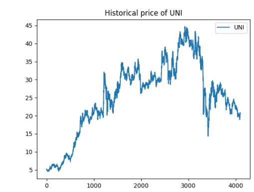
[1] A **bull** market is when the price is steadily rising. The term comes from the bull that, when attacks, strikes upward with his horns thus pushing the prices higher and higher.



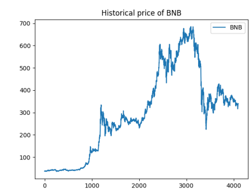
(a) Bitcoin (BTC).



(b) Ethereum (ETH).



(c) Uniswap (UNI).



(d) Binance coin (BNB).

(e) Pancakeswap (CAKE).

(f) Cardano (ADA).

(g) Monero (XMR).

Figure 2: Crypto historical data for the 7 coins of interest.

4 Implementation

4.1 Getting the data

I initially used yahoo finance python API (`https://pypi.org/project/yfinance/`) to retrieve historical cryptocurrencies data, however, the API doesn't offer historical data of all crypto I'm interested in and it's not as flexible as I wished it to be. For these reasons, I've decided to retrieve the historical data from Binance using their API [2]. Unfortunately, the API only allows request from a user i.e. to make a request you need to own a Binance account and register an

API private key. For security reasons, I can't share my API key therefore the code can't be run, unless a user registers his own key. The code is available in *load_data.py*. To run the code you will first need to install the requirements and then run using python3 as shown in Lst. 1

Listing 1: Install requirements and run python code to retrieve historical data

```
pip3 install -r requirements.txt
python3 load_data.py
```

I've decided to gather data starting from January 1 2021 to today's current day (June 12 2021). The timestep is 1 hour. The dataset contains 4099 entries for the 7 cryptocurrencies I chose. The Listing 2 reports the first 10 entries of the dataset which is available in *code/stock_1h.csv*. This data is imported into R code to fit the appropriate VAR model.

Listing 2: Head of the dataset

```
BTC,ETH,UNI,ADA,BNB,CAKE,XMR
29040.44,735.17,5.2333,0.18085,37.4215,0.6181,157.18
29458.58,749.5,5.1696,0.18394,37.6701,0.6146,160.3
29245.4,745.32,5.1926,0.18414,38.0151,0.6229,161.73
29331.51,746.14,5.167,0.18319,37.9536,0.62,160.2
29272.06,743.59,5.1178,0.18203,37.932,0.6117,160.1
29236.94,741.98,5.1255,0.18331,37.7639,0.6246,160.19
29220.31,741.02,4.9313,0.18114,37.7,0.628,159.5
29144.69,738.56,5.0076,0.17984,37.7546,0.6277,159.17
29053.75,731.46,4.9171,0.1781,37.4998,0.6199,158.98
```

4.2 Fitting a VAR model

To fit a VAR model, I've decided to use the **psychNET** R library. To chose an appropiate lag value, I've used the *Varselect()* function defined in the **vars** library. An appropiate choice is a lag of 2. Then, by fitting a VAR(2) on the data as shown in Lst. 3 and analysing the eigenvalues of the transition matrix we notice that these values are extremely close to 1. This makes the system slightly unstable and hard to deal with. Generally speaking, a proximity of the eigenvalues to 1 in such models is often due to latency trends. To check this hypothesis I've also tried to fit the VAR model using the finite differences of the data. However, I've seen no significant difference in the eigenvalues and they were still really close to 1.

Listing 3: VAR model in R

```
var3<-psychNET(stock, "GVAR",
         criterion = "EBIC",
         penalty="LASSO", lag=2)
```

[2]Binance is the biggest crypto market trader and allows to perform requests according to their API: https://docs.github.com/en/pages

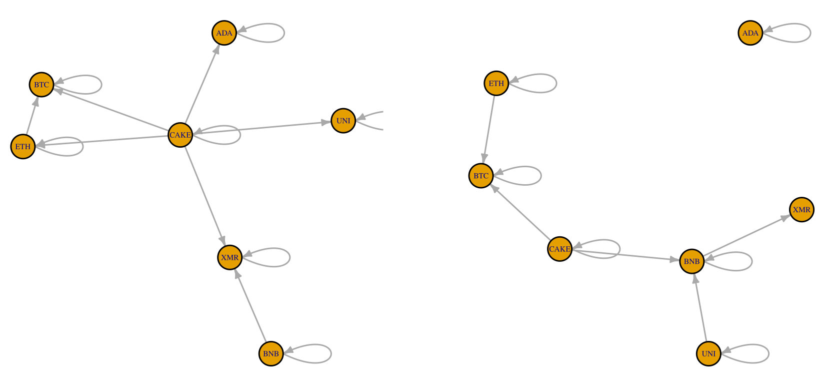
4.3 Model results

Even if the system is really close to being unstable, I managed to obtain some good result. Lst. 4 shows the ouput for the VAR model using psychNET package. We can see that there are no Conditional Dependence relationship associated to the covariance matrix of the model errors. Also, the resulting network is sparse.

Listing 4: Output of psychNET package

```
Moduli of the roots of the autoregressive companion
matrix: 1 1 0.99 0.99 0.99 0.99 0.99 0.34 0.3 0.27 0.27
0.26 0.17 0
Temporal network: TRUE
Sparsity of temporal network: 0.7142857 0.7755102
Contemporaneous network: TRUE
Sparsity of contemporaneous network: 1
```

Fig. 3 show a tight connection between BTC and ETH, however the direction of the causal relationship is flipped than what is expected: due to its high market capital the arrow should be other way around. BTC should affect ETH. ADA and XMR seem to have a marginal role in the market, they are affected by other crypto but affect none. There's a relationship between CAKE and BNB as expected (remember that the CAKE De-Fi protocol is built on top of the BNB blockchain). On the other hand I'm surprised to see no relationship between ETH and UNI.



(a) lag 1.

(b) lag 2.

Figure 3: VAR(2): lag 1 on the left and lag 2 on the right.

4.4 Conclusion

The VAR model showed partially the relationships I was expecting to see. In particular, the model didn't show any causal relationship between Uniswap (UNI) and Ethereum (ETH). This is extremely weird because the Uniswap protocol is built on top of the Ethereum blockchain. Analogously, we've seen a relationship between Pancakeswap (CAKE) and Binance blockchain (BNB). Moreover, a relationship between Ethereum and Bitcoin (BTC) was strongly expected to be the two "big players" in the market. However, what I was expecting to see was Bitcoin to have a causal relationship with all the crypto in the market and to be in the centre of the graph (i.e. where Pancakeswap instead lies). My conclusion is that the data frame I chose lead to some non-valid / contradicting conclusions. My intuition is that the price of Pancakeswap, since the beginning of the year, went from 0.60$ to 40$ and then down to 15$. The change in this price is huge (660%) compared to the change in the price of the other cryptocurrencies. This "makes" the VAR model think that Pancakeswap is the central player in the market which is far from being true. The truth is that Pancakeswap (and generally speaking De-Fi protocol) along with Uniswap are fairly new technologies and have been greatly adopted in particular in the last year. As Fig. 4 shows the amount of capital invested in De-Fi platforms has exponentially increased in the past year.

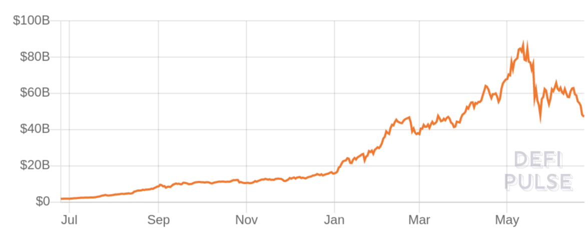


Figure 4: Capital locked in De-Fi platforms over last year.
Image gently taken from `https://defipulse.com/`

Concluding, I think that the VAR model wrongly predicted some of the causal relationships due to external causes such as the rise of De-Fi platforms. Moreover, in general, I can't exclude that there's some sort of Wyckoff's Composite Man [3]behind the scene. In the end, we only analyzed 7 cryptocurrencies which is a really small perspective to the whole market. By this, what I'm trying to say is that the data may not give a complete overview of the trading history and ongoing dynamics, resulting in a wrong prediction of the relationships between the cryptocurrencies using the VAR model.

[3]Wyckoff's Composite Man is a "mental construct" of Richard Wyckoff which is considered the pioneer of technical analysis of the stock market. The main idea behind this concept is that all the various market fluctuations and dynamics should be studied as if they were the result of a single man behind the curtain.