Collective behavior of price changes of ERC-20 tokens

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Abstract. We analyze a network constructed from tokens developed on Ethereum platform. We collect a large data set of ERC-20 token prices; the total market capitalization of the token set is 50.2 billion (10^9) US dollars. The token set includes 541 tokens; each one of them has a market capitalization of 1 million US dollars or more. We construct and analyze the networks based on cross-correlation of tokens' returns. We find that the degree distributions of the resulting graphs do not follow the power law degree distribution. We cannot find any hierarchical structures nor groupings of ERC-20 tokens in our analysis.

Keywords: Token · Cryptocurrency · Cross correlation matrix · Degree distribution.

1 Introduction

1.1 History and terminology

Econophysicists have studied complex financial systems using concepts and methods originally developed for studying physical systems [5, 10]. Such methods have also been used to study the collective behavior of price changes of various cryptocurrencies [12].

In 2009, Bitcoin started the revolution of a new form of money and introduced the concept of a blockchain - a special case of a Distributed Ledger Technology (DLT). 'Bitcoin' (with capital 'B') is a protocol and a network. The native currency of the blockchain started by Satoshi Nakamoto is known as 'bitcoin' (with lower case 'b'). The blockchain has split (or forked) into various other blockchains, and their names and currency units differ (BTC for Bitcoin, BCH for Bitcoin Cash, and BSV for Bitcoin SV). The monetary value between these different currencies varies a lot. Their respective blockchain protocols follow different rules. These different splits of the same blockchain all have the same genesis block (the first block of the entire chain) and the same blocks after the genesis block until the block that caused the split event.

There are also completely separate blockchains since the beginning of the chain: for example, Litecoin and Bitcoin do not have the same genesis block.

These completely separate blockchains can be using different rules and/or different hashing algorithms (e.g., Litecoin and Bitcoin) or they can be using the same rules and/or the same hashing algorithms (e.g., Namecoin and Bitcoin).

Ethereum blockchain introduced Turing-complete smart contracts that can be used to create programs that can be run in the supercomputer of the decentralized and distributed network. These smart contracts can be used to create new tokens. Tokens can also have monetary value. The most popular platform for tokens is the Ethereum blockchain and its Ethereum Virtual Machine (EVM) that supports smart contracts. Users are usually creating smart contracts with Solidity language. The ERC-20 standard is for creation of tokens with some basic properties. It is the most used standard for making new tokens. The ERC-20 standard gives three optional (token name, symbol, number of decimals) and six mandatory rules (totalSupply, balanceOf, transfer, transferFrom, approve, allowance) for the tokens [14].

We are using the term 'coin' to describe the native currency of a blockchain; litecoin (LTC) is the coin of Litecoin blockchain. We are using the term 'token' to describe an asset that is constructed by the methods of smart contracts; EOS (EOS) is one of the many ERC-20 tokens of Ethereum blockchain and CryptoKitties is a smart contract with non-fungible tokens following the ERC-721 standard.

Previous studies suggest that prices of some stocks are correlated [1], as are prices of cryptocurrencies [12]. Construction and analysis of networks based on correlations, or causal relationships between the characteristics of the financial instruments may be useful for such kind of applications as portfolio selection. Although there were studies on analysis of cryptocurrency cross-correlations, these studies concentrated on overall cryptocurrency market, and have not dealt with relations between Ethereum tokens. In order to fill this gap, in this paper we construct and study the network between the tokens built on the Ethereum platform.

1.2 Literature review

The econophysics book by Richmond et al. [10] introduces statistical physics, probability theory, and correlation functions. It looks at the behaviour and evolution of financial systems from the perspective of physics - or econophysics. Yet another introduction to econophysics is the book by Mantegna and Stanley [5].

The graph theory book by Bollobás [2] gives an introduction to modern graph theory.

There are lots of methods to analyze financial time series. For example, Podobnik et al. [8] use several methods to analyze the properties of volume changes $|\tilde{R}|$, and their relationship to price changes $|R|$. They analyze 14,981 daily recordings of S&P 500 Index over the period of 1950–2009, and find power-law cross-correlations between R and $|\tilde{R}|$ by using detrended cross-correlation analysis (DCCA) method [9]. This method is suitable for investigating power-law cross correlations between two simultaneously recorded nonstationary time series.

Stosic et al. [12] analyze cross correlations between price changes from data of 119 different cryptocurrencies and 200 simultaneous days in the time period from August 26, 2016 to January 18, 2018. They use methods of random matrix theory and minimum spanning trees. They find that the cross correlation matrix shows non-trivial hierarchical structures and groupings of coin/token pairs. However, they do not find such hierarchy in the partial cross correlations. They discover that most of the eigenvalues in the spectrum of the cross correlation matrix do not agree with the predictions of random matrix theory. The minimum spanning tree of cross correlations reveals distinct community structures that are quite stable. They find that the minimum spanning tree of coins and tokens consists of five communities. The conclusion is that the results represent genuine information about the cryptocurrency market, because similar communities are found for different random measurements or time periods and choices of coins and tokens or set N. It is also indicated that the communities have very different properties than the average properties of the minimum spanning tree. An application could be a lower risk cryptocurrency portfolio where cryptocurrencies are selected from distinct communities.

Boginski et al. [1] study a network representation, the market graph, of the stock market. They conduct the market graph statistical analysis and find out that it follows the power-law model. They detect cliques and independent sets in the market graph.

Plerou et al. [7] use random matrix theory methods to analyze the cross-correlation matrix C of stock price changes of the largest 1000 US companies for the period from 1994 to 1995. Their finding is that the statistics of most of the eigenvalues in the spectrum of C agree with the predictions of random matrix theory. They also find some deviations for the largest eigenvalues.

Plerou et al. [6] analyze cross correlations between price fluctuations of different stocks using methods of random matrix theory (RMT). They use two large databases for calculating cross-correlation matrices C of returns constructed from three different US stock periods. They test the statistics of the eigenvalues λ_i of C against a null hypothesis, which is a random correlation matrix constructed from mutually uncorrelated time series. Their finding is that a majority of the eigenvalues of C fall within the RMT bounds $[\lambda_-, \lambda_+]$ for the eigenvalues of random correlation matrices. They test the eigenvalues of C within the RMT bound for universal properties of random matrices. The result implies a large degree of randomness in the measured cross-correlation coefficients.

Soloviev and Belinskiy [11] construct indicators of critical and crash phenomena for cryptocurrencies. They combine the empirical cross-correlation matrix with the random matrix theory to examine the statistical properties of cross-correlation coefficients, the evolution of the distribution of eigenvalues and corresponding eigenvectors of the global cryptocurrency market. The data is the daily returns of 24 cryptocurrencies price time series from 2013 to 2018. A collective effect of the whole market is reflected by the largest eigenvalue. The proposed economic mass and the largest eigenvalue of the matrix of correlations can act like quantum indicator-predictors of falls in the cryptocurrency market.

Liang et al. [4] do a comparative analysis of cryptocurrency, foreign exchange, and stock. They took the daily close prices for about four years and construct the correlation matrices and asset trees of the markets. They conduct comparisons on volatility, centrality, clustering structure, robustness, and risk. They find that the cryptocurrency market is more fragile than the others based on the robustness and the clustering structure. For example, the clusters in the cryptocurrency market have no evident rules and they change more rapidly. For comparison, the clusters in stock market correspond to geographical regions or business sector, and the clusters in foreign exchange market match nicely with the geographical regions.

Conlon et al. [3] explore the dynamics of the equal-time cross-correlation matrix of multivariate financial time series. They examine the eigenvalue spectrum over sliding time windows and find that the dynamics of the small eigenvalues oppose those of the largest eigenvalues.

It is not known why most of the eigenvalues [12] in the spectrum of the cross correlation matrix in cryptocurrency market do not agree with the universal predictions of random matrix theory. This is in sharp contrast to the predictions for other financial markets. We investigate Ethereum's ERC-20 tokens and their network graphs to learn if similar results hold for such a subset of all the cryptocurrencies. Our research question is thus: What kind of hierarchical structures and groupings do the network graphs show for ERC-20 tokens?

2 Methods

2.1 Returns and cross correlations

To calculate the price change (or return) of a token over a time scale Δt, let us define $Y_i(t)$ as the price of a collection of tokens $i = 1, \ldots, N$ at time t. We analyze returns, defined as

$$R_i(t) \equiv \frac{Y_i(t + \Delta t) - Y_i(t)}{Y_i(t)} = \frac{Z_i(t)}{Y_i(t)}. \tag{1}$$

The problem with equation (1) is that it is sensitive to scale changes when using long time horizons [5].

The equal-time cross correlation matrix is

$$C_{ij} \equiv \langle R_i(t) R_j(t) \rangle. \tag{2}$$

$C_{ij} = 1$ is a perfect positive correlation, $C_{ij} = -1$ is a perfect negative correlation, and $C_{ij} = 0$ means no correlation [12].

2.2 Basic concepts from graph theory

Let us define a graph $G = (V, E)$ with a set of n nodes $V = \{1, ..., n\}$ and a set of m edges $E \subset V \times V$, $|V| = n$ and $|E| = m$. Each edge $e \in E$ of the graph G

has a weight $W(e) \in \mathcal{R}$. Nodes of the graph are formed by tokens for particular calendar year, weight of the edge (i, j) is equal to correlation of returns for tokens i and j. If $(i, j) \in E$, then nodes i, and j are called adjacent. If every two nodes of the graph are adjacent, the graph is called complete. Neighborhood $\mathcal{N}(v)$ of a node v is a set of all nodes v' adjacent to v, i.e. $v' \in \mathcal{N}(v)$ for all $(v, v') \in E$. Then, the degree of v, $\deg(V) = |\mathcal{N}(v)|$. For any subset of nodes $S \subseteq V$, $G[S] = (S, (S \times S) \cap E)$ denotes the *subgraph* induced by S on G. A node that belongs to S is referred to as a group node, and nodes in $V \setminus S$ are considered to be the non-group nodes. Group $G[S]$ is called a *clique* if induced by S *subgraph* is complete.

3 Results

We have collected historical data on price changes for all Ethereum's ERC-20 tokens with market capitalization higher than 1 million US dollars (USD) listed at the website Coingecko.com. Figure 1 displays log-rank plot of its market capitalization. In total, we collected data for 541 tokens, their total market capitalization is 50.2 billion USD. Overall, there were 866 cryptocurrencies with market capitalization higher than 1 million USD. The used data set did not include ether (ETH) coin itself, but it is interesting to observe that total market capitalization of Ethereum tokens exceeds that of ether, which is about 42 billion USD at the time of collection.

In order to compute correlation networks, we took the tokens that have price data for the full calendar year. In this case, it resulted in 4 tokens in 2016, 8 tokens in 2017, 111 tokens in 2018, and 333 tokens in 2019. We have computed the Pearson correlation coefficient between returns of these tokens; distributions of the resulting correlations for the two calendar years are shown in Figures 2 and 3. We created a "sliced" network by keeping only the edges formed by correlations with a value higher than the 95th percentile. As a result, we obtained three networks as described in Table 1.

year	#nodes	#edges	#components	giant component size	density	diameter
2017	8	2	6	3	0.66	2
2018	111	306	56	55	0.2	4
2019	333	2781	143	185	0.16	7

Table 1. Characteristics of the networks for 3 years. We omit the years 2015, and 2016 due to insufficient amount of data. The density and diameter are reported for the giant component.

Figures 4 and 5 show degree distributions for the networks for the years 2018 and 2019. Figures 6 and 7 show the network graphs of the tokens for the years 2018 and 2019. Also, it is interesting to observe, that graph for the year 2019 has a maximum clique size of 33 (tokens OMG, SNT, GNT, AE, BLZ, POLY, MKR,

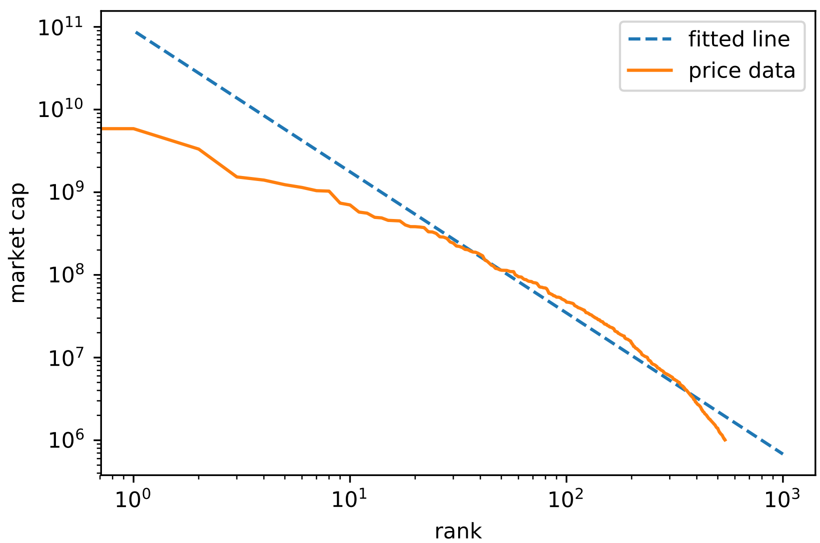

Fig. 1. Log-Rank plot of the market capitalizations of collected tokens. The plot shows the market capitalization of 541 ERC-20 tokens; from these, only 9 have market capitalization more than 1 billion USD. Dashed line shows the line fitted to the log-rank plot ($\gamma = -1.71, R^2 = 0.95$)

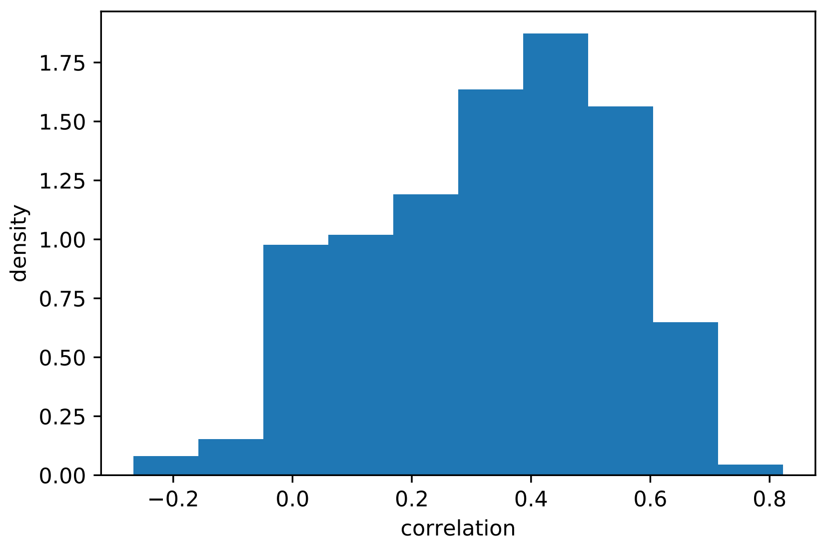

Fig. 2. The distribution of correlations for tokens of the year 2018.

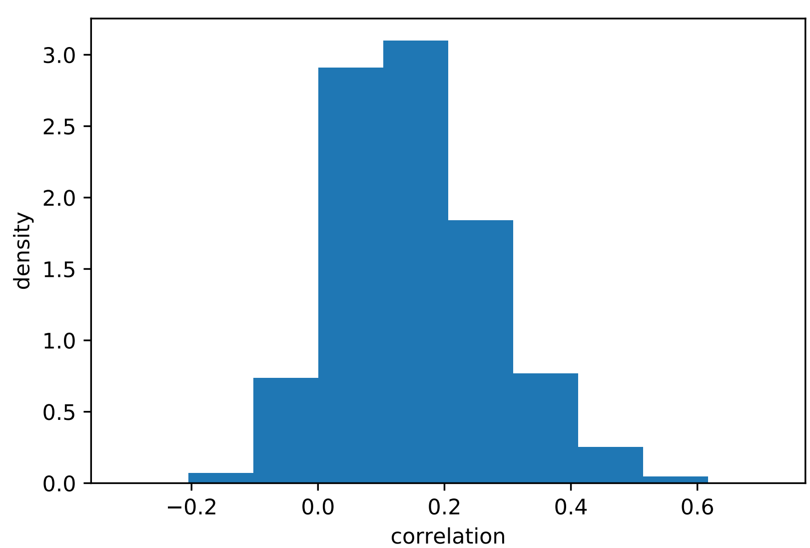

Fig. 3. The distribution of correlations for tokens of the year 2019.

ZRX, POWR, REQ, DNT, ELF, BNT, TNB, SNGLS, CND, GVT, QSP, OCN, WPR, AMB, LOOM, VIBE, MFT, STMX, QKC, VIB, GNO, BCPT, POE, WTC, YOYOW, LRC), and graph for the year 2018 has a maximum clique size of 14 (tokens BNT, CVC, POWR, OMG, LEND, STORJ, SALT, RCN, RDN, KNC, QSP, WINGS, SNM, REQ).

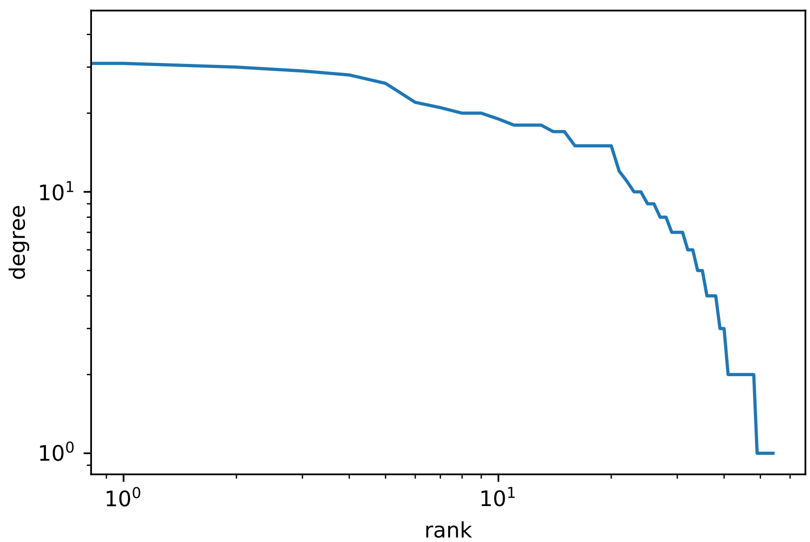

Fig. 4. The Log–Rank plot of degree distribution for the year 2018.

4 Discussion

According to Liang et al. [4] the clusters in the cryptocurrency market have no evident rules and they change more rapidly than clusters in the foreign exchange and stock markets. Do the network graphs show any hierarchical structures and groupings of ERC-20 tokens in our analysis? We can see from Figures 4 and 5 that degree distributions do not exhibit power-law behavior, that is found in many real-world graphs, including correlation networks [1]; however, there are many nodes having equally high degree. Top ten nodes with the highest degree for the years 2018 and 2019 are shown in Table 2. Total market capitalization of the ten tokens with the highest degree for the year 2018 is equal to 2.36 billion USD, and that of 2019 is equal to 2.35 billion USD, however, only two tokens are presented in both data sets: OMG and BNT.

One of the limitations of our study is the limited number of tokens; although, we have collected data on 541 tokens, our largest size graphs (for the years 2018

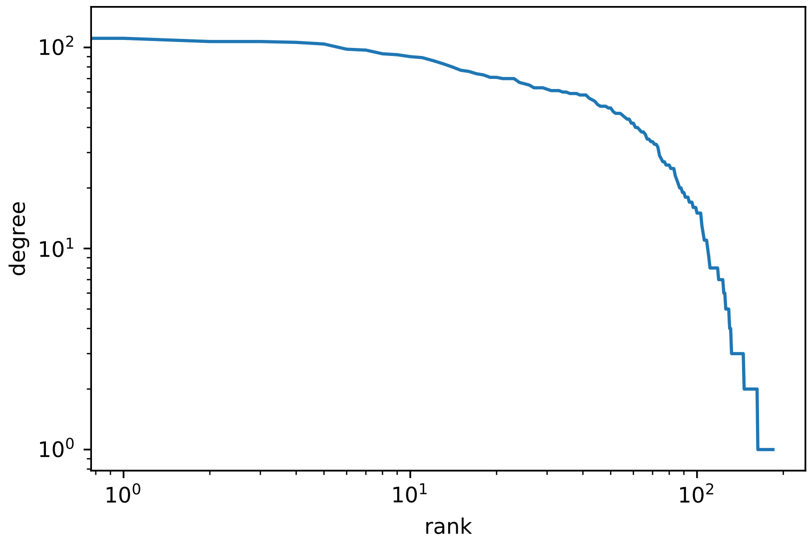

Fig. 5. The Log–Rank plot of degree distribution for the year 2019.

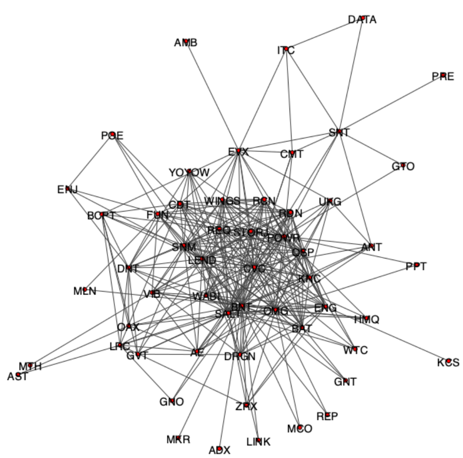

Fig. 6. The network graph of the tokens of the year 2018.

year 2018			year 2019		
name	degree	description	name	degree	description
BNT	41	Continuous liquidity and asynchronous price discovery	OMG	125	Layer-2 scaling solution for transferring value on Ethereum
CVC	31	Identity verification services	SNT	111	Status is an open source messaging platform and mobile interface to interact with DApps; the Status Network Token is a modular utility token that fuels the Status network
POWR	30	Allow access and usage of the Power Ledger Platform	GNT	107	The Golem Network Token is designed to ensure flexibility and control over the future evolution of the project; Golem is the first truly decentralized supercomputer
OMG	29	Layer-2 scaling solution for transferring value on Ethereum	MKR	107	Token for governing the Maker Protocol - the smart contracts that power Dai
LEND	28	Token for global peer-to-peer lending market	AE	106	æternity blockchain is an Erlang-based scalable smart contract platform; the Aeternity Ethereum contract expired on 2019-09-02 rendering all ERC-20 AE tokens non-transferable
SALT	26	Token for a platform for lending and borrowing	BLZ	104	An external token to represent on exchanges for customers to easily obtain to use the Bluzelle service; it is a token that bridges the Bluzelle native token (BNT) with ETH coin
SNM	22	Token on the Sonm computing power marketplace	POLY	98	Token for Polymesh, which is an enterprise-grade blockchain built for security tokens
QSP	21	Token used as the payment method for code security audits	BNT	97	Continuous liquidity and asynchronous price discovery
REQ	20	Token for participating the the Request Network, which is a decentralized network for payment requests	ELF	93	Token for a multi-chain parallel computing blockchain framework
KNC	20	Economic Facilitation, Governance, and Treasury Funds on Kyber Based Networks	ZRX	92	Token for 0x open protocol that enables the peer-to-peer exchange of assets on the Ethereum blockchain

Table 2. The top 10 nodes by degree for the years 2018 and 2019.

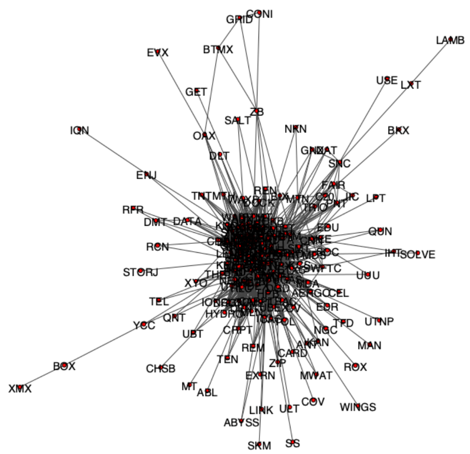

Fig. 7. The network graph of the tokens of the year 2019.

and 2019) have only 111 and 333 nodes, respectively. In future research it would be of interest to construct the networks on shorter-term price data; for example, for each 3 months, instead of one year. The equation (1) we used for calculating the returns is sensitive to scale changes for long time horizons [5].

5 Conclusions

In this paper, we made the first attempt at constructing and analyzing the network of cryptocurrencies based on their price fluctuations. Interestingly, we found that the global connectivity structure of this network does not follow a power law degree distribution that was observed for networks of stocks constructed using a similar approach [1]. Instead, the shape of our network's degree distribution resembles the one found for the Facebook social network graph [13] (although the size of the Facebook network is clearly much larger), which is an interesting observation that might be worth looking into in future work.

Furthermore, our research question was: "What kind of hierarchical structures and groupings do the network graphs show for ERC-20 tokens?" We have constructed the network from the tokens built on the Ethereum platform, but we cannot find such hierarchical structures/groupings in our analysis. Nevertheless, our preliminary results can serve as a starting point for more in-depth analysis of collective behavior of cryptocurrencies price fluctuations via network-based approaches.

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