Demythifying the belief in cryptocurrencies decentralized aspects.
A study of cryptocurrencies time cross-correlations with common currencies, commodities and financial indices

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Keywords : cryptocurrencies, fiat money, commodities, cross-correlations, dendrograms, hierarchical clustering

Abstract

The main question of this article is about whether cryptocurrencies, within their decentralization aspects, are a real commodity or/and a virtual currency. To resolve such a dilemma, we compare 7 cryptocurrencies with a sample of the three types of monetary systems: 28 fiat money, 2 commodities, 2 commodity based indices, and 3 financial market indices. We use the matrix correlation method. We display dendrograms and observe "hierarchy clustering", as a function of data coarse graining.

In fact, we confirm that the cryptocurrencies are not decentralized. We observe also that most of the currencies in the world are not significantly correlated or present a weak correlation with cryptocurrencies. Our results show that the cryptocurrency market and Forex market belong to different system communities (or regions).

1 Introduction

Decentralization is the process by which the activities of an organization, particularly those regarding planning and decision-making, are distributed or delegated away from a central, authoritative, location or group [1]: per definition, a decentralized exchange market does not rely on a third-party service to hold the funds but depends on the user's direct trades. However, according to this definition, if there are differently weighted hub nodes in a "decentralized network system", this heterogeneity could be a fundamental network weakness [2, 3], subsequently the source for a threat to decentralization. As the result of globalization which is one of today's geopolitical phenomena, it is expected that the world economic and financial society is in a quest for "decentralized currencies". The first (decentralized) cryptocurrency, Bitcoin[1] *"was created to take power out of the hands of the government and central bankers, and put it back into the hands of the people"* [5].

On the other hand, a cryptocurrency is a digital currency that uses a strong cryptography in each transaction in an exchange medium [6–8]. Thus, by essence, a cryptocurrency system does not require a central authority [9]. This means that a cryptocurrency is considered to be *de facto* decentralized. However, this is not so obvious [10, 11]. There are market based centralization aspects. In particular, governments, losing control of transactions, whence on tax revenues, wonder if they can influence the market of cryptocurrencies, since *vice versa* [10, 12], in some sense, the goal of cryptocurrency development was partially in view of avoiding country central bank controls. The control, and the lack of control, of a cryptocurrency market reminds of the destabilization effects of hubs in networks. In the latter case, the control is measured according to a "centrality index" [13]. Any kind of centralization should be considered carefully due to the 51% attack effect. In so doing, one may consider that the "decentralization property" of cryptocurrencies [14] has some analogy with the "centrality concept" in networks [13], in which hubs can be destabilized, depending on their degree of "centralization". This allows to match a classical statistical mechanics concept, "stability", with the financial one "decentralization".

Each cryptocurrency presents some appreciable difference with the common fiat currency [15–18]. First of all, the common currencies are related to a country (like GBP to UK) or group of countries (like EUR to the Eurozone countries); the related "country" has a direct influence on its currency, both politically and economically, through some "Central Bank". However, the cryptocurrencies do not relate to a specific country. Moreover, the cryptocurrencies are "liquid" and optimized for frequent, quick, and

[1] Bitcoin was born with the 2008 note from Satoshi Nakamoto [4]

small exchanges, in contrast to common currencies, for which a central authority (the "Central Bank") slows down the transaction processes. Thus, one logical way to examine if a cryptocurrency is like a fiat currency seems to be trough exchange rates with official country currencies [19–23].

Furthermore, the transactions with cryptocurrencies, using the blockchain technology, are secure and fast. "Finally", the cryptocurrencies are "private" and as a result, no one controls the currency except its active community.

Many papers have discussed the "value of cryptocurrencies" through their "price" [24, 25], searching for forecasting the cryptocurrency markets evolution, for example using tools like neural networks, to predict the price of a cryptocurrency [26], or ARCH and GARCH models for volatility modelling [27–30] or using social network concepts, to predict "volume" fluctuations in cryptocurrency transactions [31]. See also papers on how the cryptocurrency market behaves and how different market features appear in [32–34] for example.

Modeling cryptocurrency is also one of the modern subjects of studies [35], for example, searching for some collective behavior of cryptocurrency price [36]. Noticing papers on cryptography and designing the crypto market for making the system secure and efficient [37–45] may also be of interest to readers.

In this paper, we present answers to timely questions about cryptocurrencies, in particular to (i) first, what does that practically mean "currency decentralization"? (ii) What are the similitudes between cryptocurrencies and common currencies? (iii) Are they homomorphic to each other in some cases, and if so, in which cases?", (iv) How are they correlated, for example through their time series?, and (v) Is there some information from such questions (and answers) which can be drawn about the control of such a digital market?

Beside classical techniques, we approach such questions in a new way (for the present problem), i.e. through the context of hierarchy clustering and the minimum spanning tree displays [46–48].

We also search for outcomes from the correlation matrix method [49–54], by cross correlating time series of cryptocurrencies with those of Forex members.

It will be shown in the following sections that Forex currencies and cryptocurrencies, do not (unexpectedly in fact) have a significative correlation between each other. The surprise arises because it is commonly thought that some drastic economic problem arises if a country is affecting and affected by the cryptocurrency market. It is widely accepted that a cryptocurrency might loose its decentralized aspect and power in such a case. It will be shown below that some hint can be extracted out of a correlation matrix study.

In fact, it will be shown that the Forex and cryptocurrencies do not have the same correlations in different regions: we find some highly (and other necessarily less) correlated members on the world map.

2 Materials and methods

After introducing the relevant data, in view of the paper aims, it seems useful to recall some features of correlation matrices, emphasizing that they are usually random matrices indeed [50–59].

2.1 Data preparation and structure

There exist many cryptocurrencies but not all of them are well reflecting a community but one can select the most important ones, - the importance of a cryptocurrency would be "measured" by its market volume. It is reasonable to assume that the cryptocurrencies with low market capacities are not affecting the user community. Whence, we have selected the 7 cryptocurrencies, with the highest market capacities and paired them to USDT values[2]. Such most interesting cryptocurrencies are Bitcoin (BTC), Bitcoin Cash (BCC)[3], BinanceCoin (BNB), Ethereum (ETH), Lite Coin (LTC), Neo (NEO), and Quantum (QTUM); seeTable 1.

Recall that there are three common types of monetary systems: fiat money, commodity money, and commodity-based money. We compare a set of each of these to cryptocurrencies. In particular, we have selected 28 Forex time series, - all exchange rates being toward USD, from the open-access site Dukascopy (*https://www.dukascopy.com/*) and from Kibot (*http://kibot.com/*). We have chosen such 28 pairs mostly from countries with high GDP. Moreover, for completing the "sample", we have also considered 7 non-currency members, called "commodities", thereafter. These non-currency members are (i) NASDAQ-100 (here called, NSX), US Dollar Index (UDX)[4], and S&P 500 (here called, SPX), (ii) West Texas Intermediate (WTI) and Brent Crude Oil (BCO), and (iii) Silver (XAG) and Philadelphia Gold and Silver Index (XAU). Thus, "our to-be-analyzed cryptocurrency data" are going to be 42 correlation pairs, such that both

[2]USDT is a cryptocurrency asset issued on the Bitcoin blockchain via the Omni Layer Protocol. Each USDT unit is backed by a U.S Dollar held in the reserves of the Tether Limited and can be redeemed through the Tether Platform *https://www.cryptocompare.com/coins/guides/what-is-usdt-and-how-to-use-it/* cccc - which is constant over time with one dollar value for each unit.

[3]The ticker for Bitcoin Cash was first called BCC; but being used for many other meanings, it is called BCH now; some exchanges still use BCC as we do, being called Bitcoin Cash Classic; https://bitcointalk.org/index.php?topic=2617659.0

[4]The U.S. Dollar Index (USDX, DXY, DX) is an index (or measure) of the value of the United States dollar relative to a basket of foreign currencies; it can also be called USDX, DXY, or DX

crypto and fiat currencies are compared through the USD, as a common reference. The list of all these sample members can also be found in Table 1.

Cryptocurrency historical data can be obtained from the Binance cryptocurrency trading servers python-API for automated trading *https : //www.binance.com*; all such data are taken with a millisecond resolution.

The data covers two months: April and June 2018. All data in both Forex, "non-currency", and cryptocurrency starts at the same time,

We have coarse grained the exchange rates data between cryptocurrencies and USD in minute, hour and three days time intervals. One reason for which the data is so coarse grained in different time intervals stems from the fact that we wish to analyze the sample over different time scales, distinguishing between small and large time scale aspects. In so doing, one might have some hint on whether "large scale events" are affected by macro policies.

In order to have the same number of data points, in the minute and the three days time interval, we have shifted each interval by one minute and then constructed a new interval.

2.2 Mathematical methods

For constructing the correlation matrix, first we calculate the price return of each time series through

$$R[i] = log(p[i+1]) - log(p[i]), \tag{1}$$

in which $R[i]$ is each "currency pairs" return and $p[i]$ is the price at time i. Next, we have normalized $R[i]$ by the (*appropriate to the interval)* standard deviation and denoted such a normalized return as $r[i]$. As a result $r[i]$ can adopt any value but its correlation is normalized, i.e. all correlations fall in the [-1,1] interval. Thereafter, we calculate the correlation matrix elements from

$$C[i][j] = \sum_s (r[i][s] \times r[j][s]). \tag{2}$$

2.2.1 Correlation matrix and clustering

Random Matrix Theory (RMT) applications are based on the work of Wigner in nuclear physics [49]. Thereafter, many authors have demonstrated that RMT could be a good tool for studying complex systems [50–54], in particular financial assets correlation matrices [55–59] and more specifically about cryptocurrencies [14, 23], - up to finding clusters of "communities" [60–62]. Pertaining statistical properties for financial time series were discussed by Plerou et al. [63].

In order to find out if "centralized clusters" exist and how the members are distributed, we search for sub-clustering patterns also. There exist several algorithms for obtaining clusters [46,47]. The hierarchical clustering algorithm [47] classify "similar members" in lower level clusters (higher dependence) and further group clusters in higher level clusters (lower dependence). The cluster member linkage is found from and defined as have

$$\min\{dist(C_{ij}, C_{kl}), C_{ij}\&C_{kl} \in C\}, \tag{3}$$

where C is the set of the correlation matrix members, for which the metric is

$$dist(C_{ij}, C_{kl}) = \sqrt{(C_{ij} - C_{kl})^2}. \tag{4}$$

In this (Euclidean distance metric) method [64] at each step, we calculate the smallest distance between two elements of the correlation matrix and choose the nearest members (becoming "nodes") for seeding a cluster. In the next step, one looks for the nearest element of either starting nodes, and attach the new node. The process is continued till all clusters are classified and contain all members of the correlation matrix. This process, leading to a dendrogram, is illustrated in Figs. 1 - 3 for June 2018. One can at once observe some clusters.

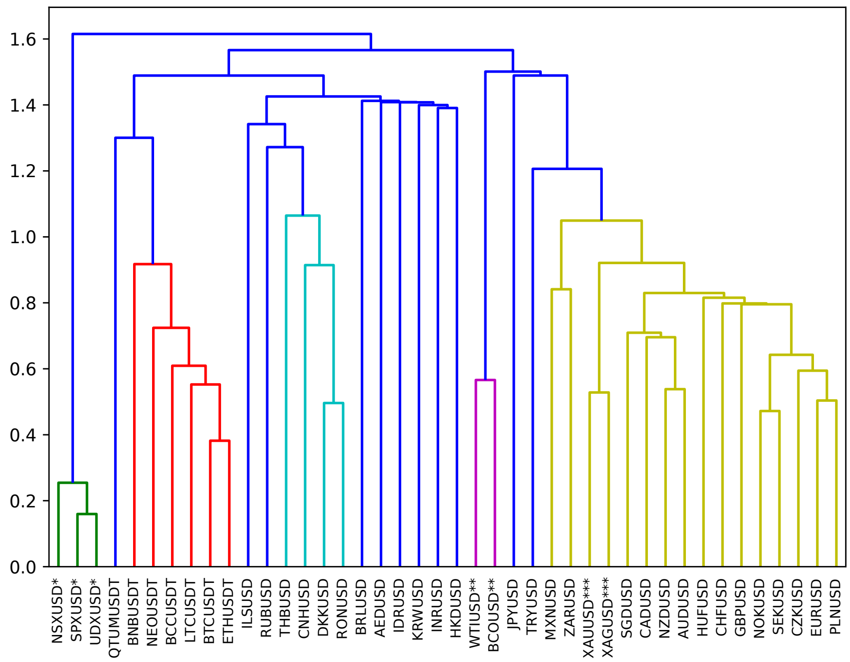

Fig 1. Dendrogram of the minute coarse graining interval exchange rates for June 2018, allowing to observe clusters (color online) at such a "small" time scale.

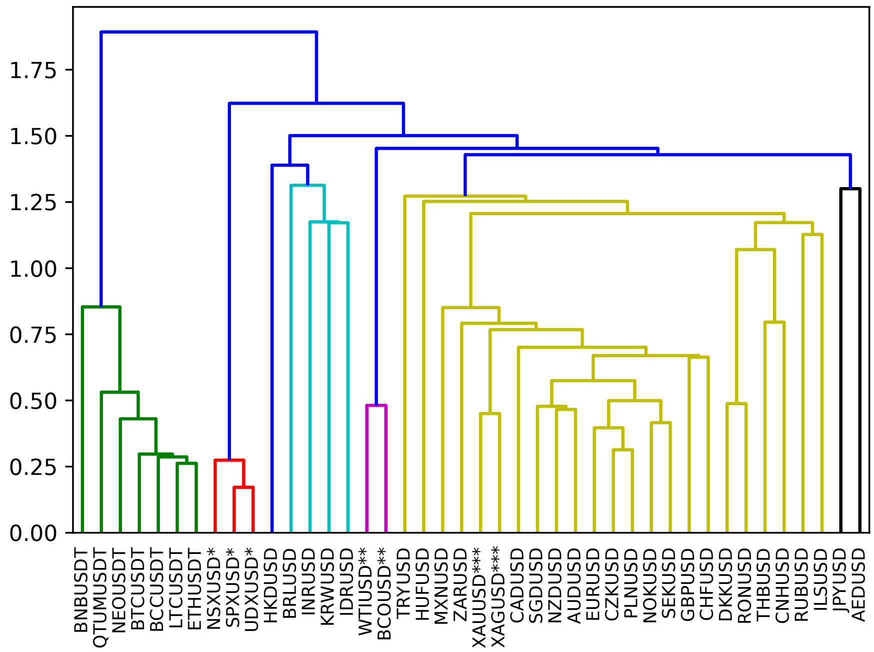

Fig 2. Dendrogram of the hour coarse graininginterval exchange rates for June 2018, allowing to observe clusters (color online) at such a "medium range" time scale.

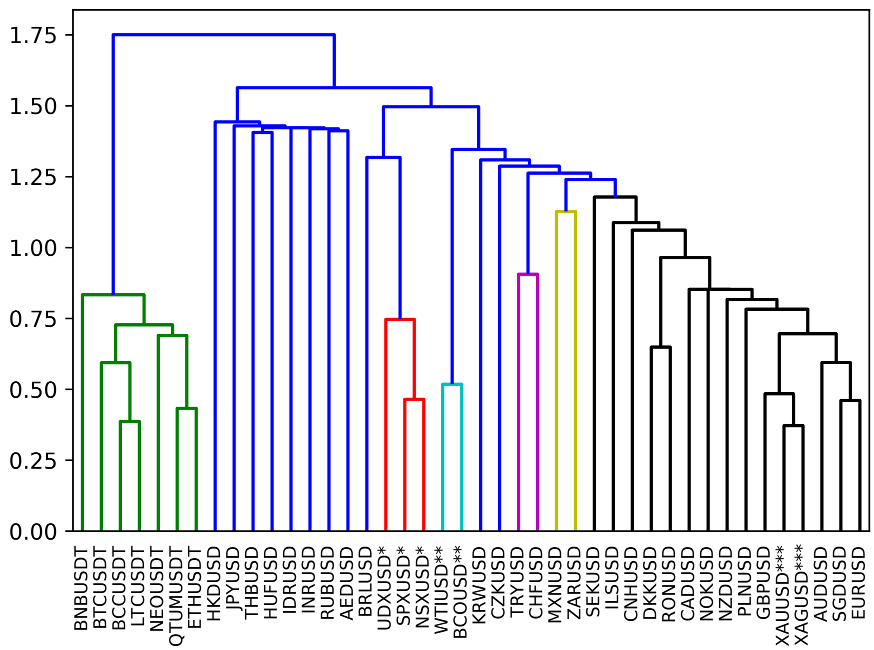

Fig 3. Dendrogram of the three days coarse graining interval exchange rates for June 2018, allowing to observe clusters (color online) at such a "large" time scale.

2.3 Remarks on Dendrograms

We pause for a few comments on the dendrograms displayed in Figs.1-3. A dendrogram shows levels of aggregation with increasing order, and can be analyzed along both x- and y-axis. The y-axis "height" represents some distance between the variables on the x-axis; one may select different heights in order to propose the existence of clusters. The lower the height, the stronger the correlation. To involve a rather arbitrary set of filters is not the primary goal here.

However it is obvious that groups appear whatever the coarse graining time. The most striking appearance is the clustering of the cryptocurrencies which are strongly tied to each other. The correlations values differ according to the coarse graining time, but not the clustering. The same goes true for the "non-currencies", although the sub-groups appear to be dispersed but they do form sub-clusters according to their type. For short coarse graining, the cryptocurrencies are also tied to the financial indices, emphasized by the only one *, at short coarse graining, but more loosely for the 3-days coarse graining. In the latter case, the (non-currency) * financial indices become tied to the "oil prices" (**). Notice that the silver and gold are loosely tied to the other non-currencies.

In brief, the short distance on the y-axis between the cryptocurrencies indicates the existence of little heterogeneity in the group, On the other "extreme", the distance between the cryptocurrencies and the oil price indicates a loose correlation.

Other comments about sub-clusters between fiat currencies, being of secondary interest in this paper are left for the reader leisure time. Nevertheless, we confirm the central role of EUR, as was already observed along time ago. [66–69].

3 Results and discussion

Following the data structure and its analysis described in Sect. 2.2 we construct the correlation matrix for the 3 different time intervals, pertinent to April and to June 2018. However, we have found out that values of the June correlation matrix lead to the same clustering as those of the April correlation matrix; thus there is no statistically significant difference between April and June, whence have omitted the latter display.

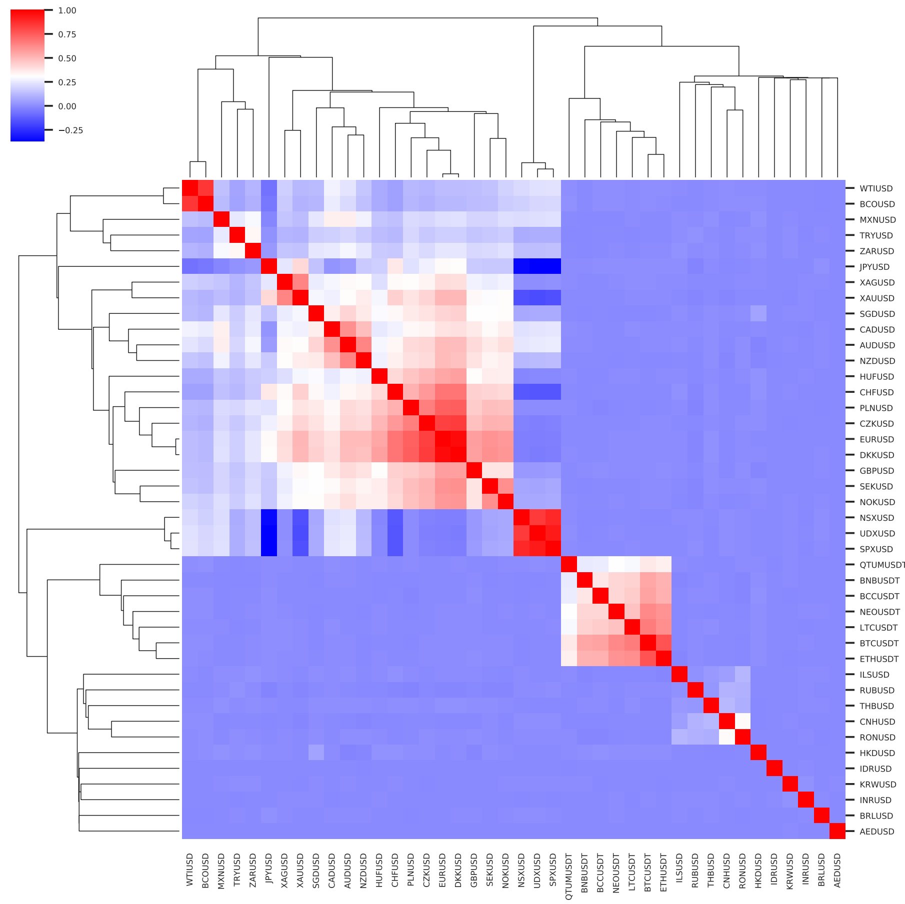

Fig 4. Correlation matrix for minute coarse graining interval exchange rates for June 2018, with the relative spanning tree, allowing to observe clusters

- The "Minute interval correlation matrix" is displayed in Fig. 4, From the shadow distribution it appears that there are distinguishable clusters. The greater is the Forex community and the smaller is the Cryptocurrency market; the latter, row 25 to 31, is markedly well grouped. The former also contains the non-currency cases, but distributed in unconnected sub-clusters: NSX, UDX, and SPX (near the center of the figure/matrix) are highly correlated with each other, while WTI and BCO are forming a sub-cluster (at the top of the figure/matrix). Moreover one can also see two correlated sub-clusters of Forex members (rows 32 to 36) and row 37 to 42, for countries (or currencies) with different economy types: the former being made of more "socialistic", the latter made with more "emerging countries".

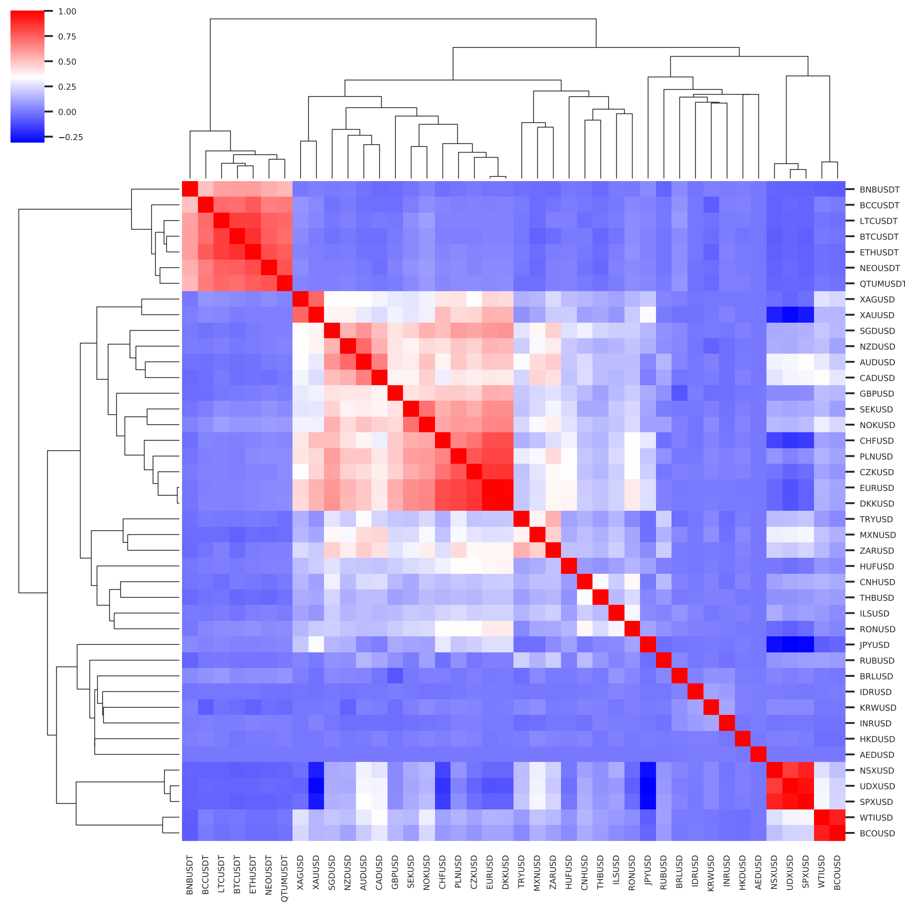

Fig 5. Correlation matrix for hour coarse graining interval exchange rates for June 2018, with the relative spanning tree, allowing to observe clusters

- The "Hour interval correlation matrix" is displayed in Fig. 5. The coupling between the Forex and the cryptocurrency increases but are still forming two distinct clusters. The non-currency members, NSX, UDX, SPX, WTI & BCO, are clustered in a group (row 38 to 42), and two other non-currency members XAU & XAG also clustered with each other (row 8 to 9). Observe some "far-off diagonal "clustering": JPY, CHF, and XAU ("column" 30, 17, and 9, respectively) present some coupling with NSX, UDX, and SPX, - which by themselves form a cluster (at the bottom of figure/matrix).

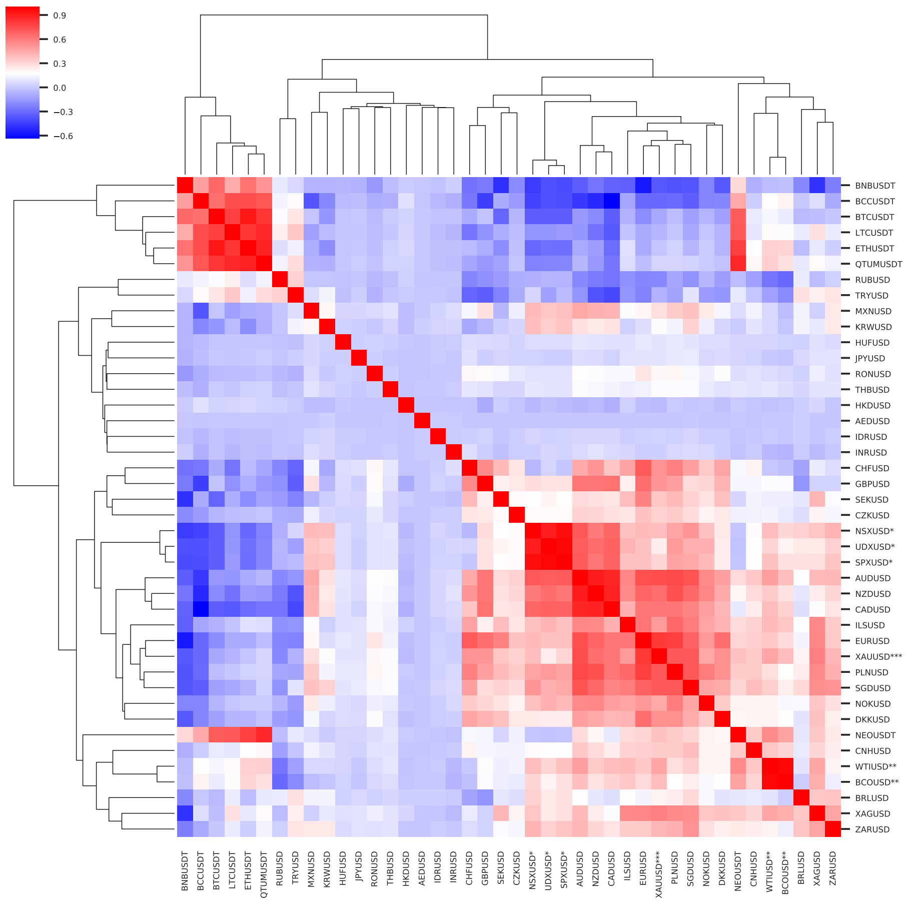

Fig 6. Correlation matrix for 3 days coarse graining interval exchange rates for June 2018, with the relative spanning tree, allowing to observe clusters

- The ”Three days interval correlation matrix” is displayed in Fig. 6. The links are tying more diversified currencies, One can observe that the cryptocurrency (top corner) and the Forex community do not have a strong link with each other anymore. NEO (sixth rank) is the only common node with a link to the Forex and the Cryptocurrency.

  The ”non-currency” members are acting more like the common currencies, in contrast with the cryptocurrency. Notice that NSX, SPX, UDX are well tied together, while WTI and BCO also form a well defined cluster; these are ”non currencies” which have a very huge market.

4 Distinguishing regions

Using each correlation coefficient between one cryptocurrency and all of the Forex members (recall, which are country specific currencies) one can find out how much a country currency affects another currency. Fig. 7 shows the correlation between Bitcoin and the currency of countries in the world, - for the 3-day time lag data. It is observed that the geographical distribution is not a homogeneous effect.

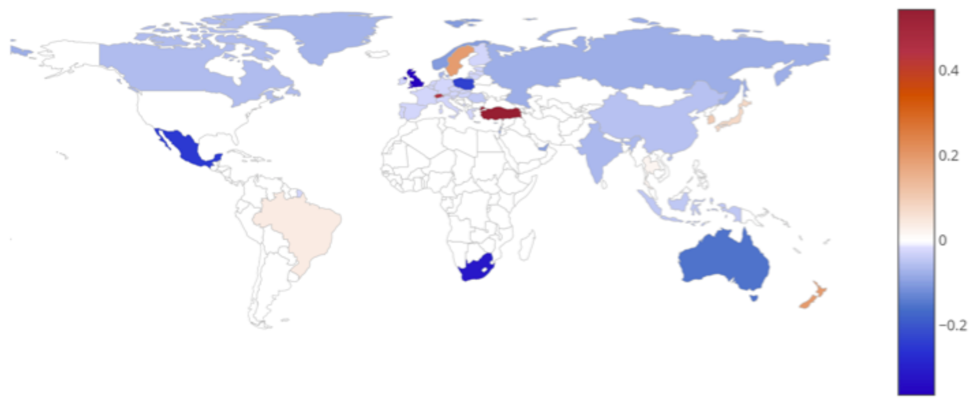

Fig 7. Distribution of correlation between the Forex members and Bitcoin over the world map in June 2018, - for the 3-day time lag data.

This is what we have expected, i.e. the "myth", for the financial bitcoin based networks, i.e. to be decentralized; each financial network is popular in a specific region but is not distributed homogeneously. We recall that all 7 cryptocurrency pairs with USDT lead to nearly the same maps either in April or June.

Nevertheless, in order to observe if any dynamical effect exists on a broader time interval, i.e. how these "correlation maps" change with time, we calculated the evolution of sample member correlations with the Bitcoin cash (BCC) between Jan. 2018 and Aug. 2018; a few (*bona fide currencies*) exchange rates correlation values are displayed on Fig 8, -specifically for the 3-days coarse graining cases. For completeness, let it be mentioned that the illustrated BCC result is statistically similar to the other 6 Cryptocurrencies members, listed in Table 1. It is seen that one can distinguish two types of currencies. There are "currencies" which change much more with time than some others. We may classify currencies as dynamic or numb. The numb currencies include RUB, JPY, TRY, CNH and EUR; they are "constant" through time, while dynamical currencies, such as CHF, GBP, CAD, AUD and NZD are changing with time. TRY which was in the numb group, up to July, next rises to its highest point in August,[5] while JPY always seems

[5] see comment in Appendix

to be stacked in numb group.

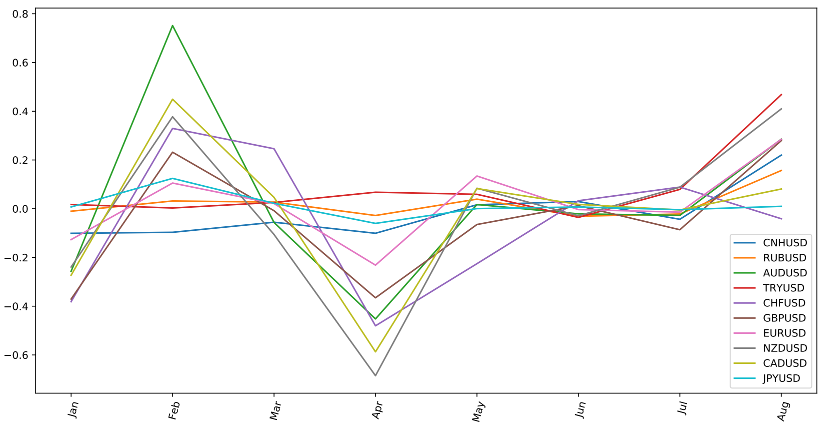

Fig 8. Temporal correlations between several Forex members and the Bitcoin Cash (BCC) currency, between Jan. 2018 and Aug. 2018, - for the 3-day time lag data, thereby illustrating that one can classify currencies as either dynamical or numb through their exchange rate with cryptocurrencies.

5 Conclusions

In this reported research, we have examined correlation matrices, made of a set of exchange rates and values of various financial items, measured over different time intervals, with respect to cryptocurrency behavior. We have wondered whether such cryptocurrencies are like real currencies, or like "commodities", thus "virtual currencies", searching for the correlations and evolutions of relevant exchange rates. In so doing, we propose some consideration about the decentralized aspects, or expectations, of cryptocurrencies. Thus, we chose many cases such that one could conclude about a "universality content" of the answers to our questions.

First, we have found a strong clustering of the cryptocurrencies. The correlations values differ according to the coarse graining time, but not the clustering. The cryptocurrencies are also tied to the financial indices, at short coarse graining, but more loosely for the 3-days coarse graining

On the other hand, it is observed that there is an apparently steady state pattern for the real Forex exchanges; whatever the month an approximately similar pattern occurs. The cryptocurrency exchange looks also like to be in a steady state. But the exchanges between Forex and Cryptocurrency are not in an equilibrium-like state. The situation appears to depend on various parameters, likely depending on, and likely influenced by, the Economic Policies of the various countries in the world .

Indeed, from both types of analysis, we find out that the cryptocurrency members correlation are not distributed homogeneously all around the world. This is deduced from the network geographical distribution. One could have expected that such a "currency network" is distributed around the world rather uniformly. Clusters exist for short time scales and are rather stable for the examined time intervals. This observation implies that having such high power multi-hub nodes might be a threat to the decentralization hypothesis concept or belief.

We conclude, due to the appearance of sub-clusters in the Forex and the Cryptocurrency clusters, from the correlation matrix, from dendrograms, and also from the stability of clusters made of sample ("commodity") members like gold, silver and oil (represented by BCO, WTI and XAU) that cryptocurrencies neither have a social ("financial") acceptability to be like a classical currency up to now, nor are acting like a common commodity.

As a bonus, it is observed that there exist some patterns on different time scales in the cryptocurrency community correlations with Forex cases. But the Forex and cryptocurrency are not steadily correlated with each other over time. There exist some "dynamic currencies" and some "numb currencies" in temporal correlation with some fiat currencies, as presented here from the BCC point of view[6].

Appendix

In this Appendix, following a reviewer comment, we mention some extra information, on some specific country, Turkey, and its money TKY behavior, - as observed in the main text. We quote the reviewer comment : *the issue of the Turkish Lira (TRY) needs clarification: in Fig.7 TRY/USD has a correlation of 0.4 to BTC in June 2018 while in Fig.8 for the Bitcoin Cash such a correlation is close to null in the same month. ... such a big difference in correlation looks suspicious.* This comment on the TRY is interesting. In order to sustain the findings, we have redone some technical check. Using 3 sine waves with different phases ($\omega t, \omega t \pm 60$), we find a positive correlation between Wave No.2 and both waves No.1 and No.3. But there is a negative correlation between waves No.1 and No.3. Notice also in Fig.8, that one finds that TRY and BCC have an about 0.4 correlation in August 2018. We conjecture that the "delay" maybe depending on Turkey-based activities in the crypto market. We tie this time lag to the value of Turkey's currency which has nosedived since January and lost more than 34% of its value against the dollar at the beginning of August. We don't take side on political

[6] The TRY is a currency which was in numb group, in April but in June of 2018, started to rise up. This may be due to the influence of geopolitical phenomena. We are all aware that Turkey had some conflict with USA on these days. Thus, our correlation approach method seems of interest also for considering images of conflicts between cryptocurrencies and fiat currencies; see Appendix also.

aspects, but we quote W. Suberg (https://cointelegraph.com/news/turkish-liras-collapse-sees-media-highlight-bitcoins-relative-stability) *"According to data from Google Trends, interest in Bitcoin increased markedly in August, while local exchanges have seen volumes explode by over 150 percent this week alone."* See also K. Sedgwick $https://news.bitcoin.com/turkish-bitcoin-volume-oars-as-traders-flee-the-lira/$

Interestingly, this comment reinforces the need to find an answer to the question about the "financial decentraliized" aspect of cryptocurrencies, and its analysis through a network description involving countries as hubs with some "centrality" concept, whence whether political rules can interfere with the decentralization goals. Notice also at this time of revising the paper that "*the Turkish lira fell by 1% to 7.26 against the dollar, on May 7, 2020, surpassing the previous record low of 7.24 reached during the August 2018 currency crisis.The Turkish currency has lost some 18% of its value against the dollar since the beginning of the year."* We quote $https://apnews.com/4b106ebbc1d1a6c01796c2a2bd33c6be$. Thus, within some (research) time lag, it would be interesting to come back to this point!

Acknowledgments

Thanks to Kibot for kindly giving us the data of some Forex pairs

References

1. UNDP. "Decentralization: a sampling of definitions". Working Paper (1999).

2. Grilli, Ruggero, Gabriele Tedeschi, and Mauro Gallegati. "Business fluctuations in a behavioral switching model: gridlock effects and credit crunch phenomena in financial networks." Journal of Economic Dynamics and Control 114, 103863 (2020)..

3. Rotundo, Giulia, and Andrea Scozzari. "Co-evolutive models for firms dynamics." In Networks, topology and dynamics, pp. 143-158. Springer, Berlin, Heidelberg, 2009.

4. Nakamoto, Satoshi "Bitcoin: A Peer-to-Peer Electronic Cash System". 2008 Working paper

5. Gilpin, L. "10 things you should know about Bitcoin and digital currencies". TechRepublic. (2014) Retrieved from http://www.techrepublic.com/article/10-things-you-should-know-about-bitcoin-and-digitalcurrencies/

6. Greenberg, Andy "Crypto Currency". Forbes.com. Retrieved 2020.

7. Chohan, Usman W. "Cryptocurrencies: A Brief Thematic Review". Archived 25 December 2017 at the Wayback Machine. Economics of Networks Journal. Social Science Research Network (SSRN). Date accessed 28 August 2017.

8. Schueffel, Patrick. "Taming the beast: a scientific definition of fintech." Journal of Innovation Management 4(4), 32-54 (2016).

9. Lansky, Jan. "Possible State Approaches to Cryptocurrencies". Journal of Systems Integration 9, 19–31 (2018).

10. Gervais, Arthur, Ghassan O. Karame, Vedran Capkun, and Srdjan Capkun. "Is bitcoin a decentralized currency?." IEEE Security & Privacy 12(3), 54-60 (2014).

11. Beikverdi, Alireza and JooSeok Song, "Trend of centralization in Bitcoin's distributed network," 2015 IEEE/ACIS 16th International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD), Proceedings pp. 1-6.

12. Butts, Carter T. "Exact bounds for degree centralization." Social Networks 28(4), 283-296 (2006).

13. Freeman, Linton C. "Centrality in social networks: Conceptual clarification." Social Networks 6, 223-258 (1979).

14. Drożdż, Stanisław, Ludovico Minati, Paweł Oświęcimka, Marek Stanuszek, and Marcin Wątorek. "Competition of noise and collectivity in global cryptocurrency trading: Route to a self-contained market." Chaos 30(2), 023122 (2020).

15. Ammous, Saifedean, "Can Cryptocurrencies Fulfil the Functions of Money?". The Quarterly Review of Economics and Finance 70, 38-51 (2018).

16. Böhme, Rainer, Nicolas Christin, Benjamin Edelman, and Tyler Moore. "Bitcoin: Economics, Technology, and Governance". Journal of Economic Perspectives, 29(2), 213-238 (2015).

17. Sovbetov, Yhlas. "Factors Influencing Cryptocurrency Prices: Evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero". Journal of Economics and Financial Analysis 2(2), 1-27 (2018).

18. Pieters, Gina, and Sofia Vivanco. "Financial regulations and price inconsistencies across Bitcoin markets". Information Economics and Policy, 39, 1-14 (2017).

19. Szetela, Beata, Grzegorz Mentel, and Stanisław Gędek, “Dependency analysis between bitcoin and selected global currencies.” Dynamic Econometric Models 16(1), 133-144 (2016).

20. Corelli, Angelo. “Cryptocurrencies and exchange rates: A relationship and causality analysis,” Risks 6(4), 111 (2018).

21. Corbet, Shaen, Andrew Meegan, Charles Larkin, Brian Lucey, and Larisa Yarovaya, “Exploring the dynamic relationships between cryptocurrencies and other financial assets.” Economics Letters 165, 28-34 (2018).

22. Drożdż, Stanisław, Ludovico Minati, Paweł Oświęcimka, Marek Stanuszek, and Marcin Wątorek. "Signatures of the crypto-currency market decoupling from the Forex.” Future Internet 11(7), 154 (2019).

23. Drożdż, Stanisław, Robert Gębarowski, Ludovico Minati, Paweł Oświęcimka, and Marcin Wątorek. "Bitcoin market route to maturity? Evidence from return fluctuations, temporal correlations and multiscaling effects.” Chaos: An Interdisciplinary Journal of Nonlinear Science 28(7), 071101 (2018).

24. Bouoiyour, Jamal, Refk Selmi, Aviral Kumar Tiwari, and Olaolu Richard Olayeni. ‘What drives Bitcoin Price?’. Economics Bulletin, 36(2), 843-850 (2016).

25. Polasik, Michal, Anna Iwona Piotrowska, Tomasz Piotr Wisniewski, Radoslaw Kotkowski, and Geoffrey Lightfoot. "Price fluctuations and the use of Bitcoin: An empirical inquiry". International Journal of Electronic Commerce 20(1), 9-49 (2015).

26. Spilak, Bruno. "Deep neural networks for cryptocurrencies price prediction". A thesis submitted for the degree of Master of Science, Humboldt-Universität zu Berlin. May 21, 2018

27. Glaser, Florian, Kai Zimmermann, Martin Haferkorn, Moritz Christian Weber, and Michael Siering, "Bitcoin - Asset or currency? Revealing users’ hidden intentions". In: Twenty Second European Conference on Information Systems, ECIS 2014, Tel Aviv, 1-14 (2014).

28. Chu, Jeffrey, Stephen Chan, Saralees Nadarajah, and Joerg Osterrieder. "GARCH Modelling of Cryptocurrencies". Journal of Risk and Financial Management, 10(4), 17 (2017).

29. Dyhrberg, Anne Haubo "Bitcoin, gold and the dollar–A GARCH volatility analysis". Finance Research Letters, 16, 85-92 (2016).

30. Cerqueti, Roy, Massimiliano Giacalone, and Raffaele Mattera, "Skewed non-Gaussian GARCH models for cryptocurrencies volatility modelling." Information Sciences, 527, 1-26, (2020).

31. Kim, Young Bin, Jun Gi Kim, Wook Kim, Jae Ho Im, Tae Hyeong Kim, Shin Jin Kang, and Chang Hun Kim. "Predicting Fluctuations in Cryptocurrency Transactions Based on User Comments and Replies". PLOS One (2016) e0161197.

32. Liang, Jiaqi, Linjing Li, and Daniel Zeng. "Evolutionary dynamics of cryptocurrency transaction networks: An empirical study". PLOS (2018) e0202202.

33. Poyser, Obryan. "Herding behavior in cryptocurrency markets". arXiv:1806.11348v1.

34. González, María De La O, Francisco Jareño, Frank S. Skinner. "Nonlinear Autoregressive Distributed Lag Approach: An Application on the Connectedness between Bitcoin Returns and the Other Ten Most Relevant Cryptocurrency Returns." Mathematics 8, 810 (2020).

35. Sockin, Michael, and Wei Xiong. "A Model of Cryptocurrencies". NBER Working Paper No. 26816, March 2020.

36. Stosic, Darko, Dusan Stosic, Teresa B. Ludermir, and Tatijana Stosic. "Collective behavior of cryptocurrency price changes". Physica A: Statistical Mechanics and its Applications 507, 499-509 (2018).

37. Massias, Henri, X. Serret Avila, and J-J. Quisquater. "Design of a secure time-stamping service with minimal trust requirements". 20th Symposium on Information Theory in the Benelux (1999). A. Barbé; E. C. van der Meulen, P. Vanroose, Eds. (Enschede, Netherlands : Werkgemeenschap voor Informatie- en Communicatietheorie, 1999)

38. Haber, Stuart, and W. Scott Stornetta. "How to time-stamp a digital document" Journal of Cryptology 3, 99-111 (1991).

39. Bayer, Dave, Stuart Haber, and W. Scott Stornetta. "Improving the efficiency and reliability of digital time-stamping" in Sequences II: Methods in Communication, Security and Computer Science, 329-334 (1993).

40. Haber, Stuart, and W. Scott Stornetta. "Secure names for bit-strings". Proceedings of the 4th ACM Conference on Computer and Communications Security, pp. 28-35, April 1997

41. Merkle, Ralph C. "Protocols for public key cryptosystems". Proc. 1980 Symposium on Security and Privacy, IEEE Computer Society, pp.122-133, April 1980.

42. Li, Xin, and Chong Alex Wang. 'The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin'". Decision Support Systems, 95, 49-60 (2017).

43. De Filippi, Primavera, and Benjamin Loveluck. The invisible politics of Bitcoin: governance crisis of a decentralised infrastructure. Internet Policy Review, 5(3), 1-28 (2016).

44. De Filippi, Primavera. 'Bitcoin: A Regulatory Nightmare to a Libertarian Dream', Internet Policy Review, 3(2), 1-12 (2014).

45. Wright, Aaron, and Primavera De Filippi 'Decentralized Blockchain Technology and the Rise of Lex Cryptographia', SSRN, 2(1), 1-58 (2015).

46. Yu, Meichen, Arjan Hillebrand, Prejaas Tewarie, Jil Meier, Bob van Dijk, Piet Van Mieghem, and Cornelis Jan Stam. "Hierarchical clustering in minimum spanning trees". Chaos 25, 023107 (2015).

47. Szekely, Gabor J., and Maria L. Rizzo. "Hierarchical clustering via Joint Between-Within Distances: Extending Ward's Minimum Variance Method". Journal of Classification 22 (2), 151-183 (2005).

48. Francés, Carlos Jaureguizar, Pilar Grau-Carles, and Diego Jaureguizar Arellano. "The cryptocurrency market: A network analysis." Esic Market Economics and Business Journal 49 , 569-583 (2018).

49. Wigner, Eugene P. "On a class of analytic functions from the quantum theory of collisions". Annals of Mathematics 53(1), 36-67 (1951).

50. Dyson, Freeman J. "A Brownian-motion model for the eigenvalues of a random matrix". Journal of Mathematical Physics 3, 1191-1198 (1962).

51. Dhesi, Gurjeet and R. Clark Jones "Asymptotic corrections to the Wigner semicircular eigenvalue spectrum of a large real symmetric random matrix using the replica method". Journal of Physics A: Mathematical and General 23 (1990) 5577-5599.

52. Drożdż, Stanisław, Jaroslaw Kwapień, Josef Speth, and M. Wójcik, "Identifying complexity by means of matrices." Physica A 314, 355-361 (2002).

53. Jafari, Gholamreza, Amir Hossein Shirazi, Ali Namaki, and Reza Raei. "Coupled time series analysis: methods and applications". Computing in Science & Engineering 13, 84-89 (2011).

54. Jamali, Tayeb, and G. Reza Jafari. "Spectra of empirical autocorrelation matrices: A random-matrix-theory-inspired perspective". Europhysics Letters (EPL) 111, 10001 (2015).

55. Laloux, Laurent, Pierre Cizeau, Jean-Philippe Bouchaud, and Marc Potters. "Noise dressing of financial correlation matrices". Physical Review Letters 83, 1467 (1999).

56. Plerou, Vasiliki, Parameswaran Gopikrishnan, Bernd Rosenow, Luis A. Nunes Amaral, Thomas Guhr, and H. Eugene Stanley. "Random matrix approach to cross correlations in financial data" Physical Review E 65, 066126 (2002).

57. Namaki, Ali, Gholamreza Jafari, and Reza Raei. "Comparing the structure of an emerging market with a mature one under global perturbation". Physica A 390, 3020-3025 (2011).

58. Namaki, Ali, Reza Raei, and Gholamreza Jafari. "Comparing Tehran stock exchange as an emerging market with a mature market by random matrix approach". International Journal of Modern Physics C 22, 371-383 (2011).

59. Mobarhan, N.S. Safavi, Ali Saeedi, F. Rahnamay Roodposhti, and Gholamreza Jafari. "Network trending; leadership, followership and neutrality among companies: A random matrix approach". Physica A 462, 858-863 (2016).

60. Ausloos, Marcel, and Renaud Lambiotte. "Clusters or networks of economies? A macroeconomy study through gross domestic product". Physica A: Statistical Mechanics and its applications 382, 16-21 (2007).

61. Gligor, Mircea, and Marcel Ausloos. "Cluster structure of EU-15 countries derived from the correlation matrix analysis of macroeconomic index fluctuations". The European Physical Journal B 57, 139-146 (2007).

62. Gligor, Mircea, and Marcel Ausloos. "Convergence and cluster structures in EU area according to fluctuations in macroeconomic indices". Journal of Economic Integration 23, 297-330 (2008).

63. Plerou, Vasiliki, Parameswaran Gopikrishnan, Bernd Rosenow, Luís A. Nunes Amaral, and H. Eugene Stanley. "Universal and nonuniversal properties of cross correlations in financial time series". Physical Review Letters 83, 1471-1474 (1999).

64. Miškiewicz. Janusz. "Distance matrix method for network structure analysis". Statistical Tools for Finance and Insurance. Springer, Berlin, Heidelberg, pp. 251-289 (2011).

65. Cerqueti, Roy, Giulia Rotundo, and Marcel Ausloos. "Investigating the configurations in cross-shareholding: a joint copula-entropy approach". Entropy 20, 134 (2018).

66. Ausloos, Marcel, and Kristinka Ivanova. "Correlations between reconstructed EUR exchange rates versus CHF, DKK, GBP, JPY and USD". International Journal of Modern Physics C 12(2), 169-195 (2001).

67. Ivanova, Kristinka and Marcel Ausloos. "Are EUR and GBP different words for the same currency?". The European Physical Journal B-Condensed Matter and Complex Systems 27(2), 239-247 (2002).

68. Ivanova, Kristinka, and Marcel Ausloos. "False EUR Exchange Rates vs. DKK, CHF, JPY and USD". In Empirical Science of Financial Fluctuations, pp. 51-60. Springer, Tokyo, 2002.

69. Ausloos, Marcel and Ivanova, Kristinka. "Classical technical analysis of Latin American market indices: correlations in Latin American currencies (ARS, CLP, MXP) exchange rates with respect to DEM, GBP, JPY and USD". Brazilian Journal of Physics 34(2A), 504-511 (2004).

Data List		
Cryptocurrency	Forex	Non-currency
Bitcoin Cash (BCC)	United Arab Emirates Dirham (AED)	*NASDAQ-100 (NSX)
Binance Coin (BNB)	Australian Dollar (AUD)	*U.S. Dollar Index (UDX)
Bitcoin (BTC)	Brazilian Real (BRL)	*S&P 500 Index (SPX)
Ethereum (ETH)	Canadian Dollar (CAD)	**Crude Oil (WTI)
Lite Coin (LTC)	Swiss Franc (CHF)	**Brent Oil (BCO)
Neo (NEO)	China Offshore Spot (CNH)	***Silver (XAG)
Quantum (QTUM)	Czech Koruna (CZK)	***PHLX Gold/Silver Sector Index (XAU)
	Danish Krone (DKK)	
	Euro (EUR)	
	Pound Sterling (GBP)	
	Hong Kong Dollar (HKD)	
	Hungarian Forint (HUF)	
	Indian Rupee (INR)	
	Indonesian Rupiah (IDR)	
	Israeli New Shekel (ILS)	
	Japanese Yen (JPY)	
	South Korean Won (KRW)	
	Mexican Peso (MXN)	
	New Zealand Dollar (NZD)	
	Norwegian Krone (NOK)	
	Poland New Zloty (PLN)	
	Romanian Leu (RON)	
	Russian Ruble (RUB)	
	Swedish Krona (SEK)	
	Singapore Dollar (SGD)	
	Thai Baht (THB)	
	Turkish Lira (TRY)	
	South African Rand (ZAR)	

Table 1. Sample members; the number of * in the third column allows to distinguish different types of "non-currency" cases.