The cryptocurrency market: 
A network analysis

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Abstract

In this paper we examine the characteristics of the daily price series of 16 different cryptocurrencies between July 2017 and February 2018. The methodologies used for the analysis are the so-called Minimum Spanning Tree (MST) and hierarchical analysis by dendrogram, both obtained from Pearson correlations between daily returns. This methodology visualizes the market relationships between the assets analyzed, identifying a high correlation between price movements for all the currencies. In addition, it has been possible to identify Ethereum’s position as a benchmark currency in the cryptocurrency market, rather than Bitcoin, as one might expect, due to its popularity and trading volume.

Keywords: cryptocurrency; Minimum Spanning Tree (MST); correlations; cluster; topology.

JEL codes: G12, G41.
有关加密货币市场的网络分析

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文章摘要
本研究探讨从二零一七年七月至二零一八年二月期间的十六种加密货币每日价格系列的特点。本研究利用最小生成树（MST）和通过树状图的阶层分法作为分析方法，从每日回报之间的皮尔森相关系数获得两者。此方法能具体呈现被分析的资产之间的市场关系，结果显示在所有加密货币的价格变动之间都存在着甚高的相关系数。此外，结果能够验证作为加密货币市场参考的Ethereum的部位，其代替了大众期待，比较流行和交易量大的比特币（Bitcoin）作为参考加密货币。

关键词: 加密货币、最小生成树、相关系数、聚类、拓扑学。

JEL 分类号: G12、G41。

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1. Introduction

The cryptocurrencies markets are attracting growing interest from the media, investors and regulators. Some of the characteristics attributed to them are their simplicity, transparency and variety of potential uses, ranging from methods of payment to the possibility of being used for the development of applications. Katsiampa et al (2018) define cryptocurrency as “a digital asset designed to work as a means of exchange using cryptography to secure transactions without being subject to any government intervention.” Although the Bitcoin is the currency with the highest level of capitalization (56% in 2018), there are more than 1,900 cryptocurrencies, as can be seen on the coinmarketcap.com website. Of these, more than 300 amount to over $10m of capitalization, 66 over $100m and 16 over $1bn.

Despite the growing interest in these financial assets, the academic information is insufficient and most of it is centred on the analysis of the most popular and oldest cryptocurrency, the Bitcoin, which is the currency with the longest time series in terms of price and volume of transactions.

This is the case of some of the recent studies focussed on the analysis of volatility. Baek et al. (2015) analyzed the relative volatility between Bitcoin and the SP500 index. Katsiampa (2017) and Chu et al. (2017) attempted to study Bitcoin volatility using GARCH models. On the other hand, Urquhart (2017) studied the price clustering of Bitcoin. Some other studies have sought relationships between a number of cryptocurrencies; Huynh (2017) used models with GARCH-Copula between three currencies, and Bouoiyour and Selmi (2017) sought to explain whether there is an association between the Ether and Bitcoin using GARCH-Copula models. Osterrieder et al. (2017) examined the relationship between some crypto currencies through various models, which also include GARCH-Copula. On the other hand, Phillip et al. (2017) studied the volatility in the series of price returns on various cryptocurrencies and Gkillas et al. (2018) and Feng et al. (2018) used extreme value theory to model the behaviours of these series. Similarly, Balcilar et al. (2017) and Katsiampa et al (2018) examined the relationship between volume and yield for both Bitcoin and a broader sample of currencies, respectively.

The objective of this paper is to analyze the cryptocurrency market and its dependencies using two different techniques. The first consists of creating the MST (Minimum Spanning Tree), which is a graph whose elements or nodes will be cryptocurrencies and whose links are constructed from the Pearson correlation matrix, following the technique proposed by Mantegna (1999). This technique has provided reliable results in the study of financial markets, making it possible to significantly classify assets into hierarchical clusters [see Bonano et al. (2000), McDonald et al. (2005), Naylor et al. (2007), Kwapien et al. (2009), Aste et al. (2010), Song et al. (2011), Vizgunov et al. (2014) and Wang et al. (2018) among others]. In addition, this methodology is robust when it comes to solving the empirical problem of noise in a matrix of historical correlation, as demonstrated by Onnela et al. (2003) in his McDonald analysis. Also, this type of analysis involves the construction of a
network in which some nodes interact and affect each other, so this technique can analyse the degree of co-operations between the cryptocurrencies and identifies the currencies that have a greater influence on the fluctuations in prices and in the market as a whole.

The second technique consists of the analysis of the hierarchical structure of the network by constructing a dendrogram, grouping the currencies into clusters according to their behaviour in the market.

The study adopts a novel approach because it proposes a complete network of connections based on correlations for the cryptocurrency market. It should be noted that the analysis of correlations is not uncommon in finance. In fact, its use is widespread in portfolio selection models and risk management models. Thus, correlation analysis has played an important role in establishing the relationship between the benefits of diversification and market volatility. Therefore, knowledge of the correlations in a financial market - and in cryptocurrencies in particular - can help investors to understand price formation mechanisms and also serve as a guide in diversifying their portfolios.

This paper is structured as follows: the following section describes the data used. Point 3 describes the methodology for the construction of the MST. Section 4 presents the main results obtained and the study ends by summarizing the main conclusions obtained.

2. Material and methodology

Of the total of more than 1500 cryptocurrencies that are referenced in the main source of price data, the webpage www.coinmarketcap.com, the 16 whose total volume was most representative have been selected. This website, in turn, collects data from the different markets (In September 2018 there were 400 markets or exchanges where Bitcoin was listed, as compared with, for example, only 5 in a low capitalization currency such as ZClassic.) On the date of commencement of this study, October 2017, the 16 largest volumes at that time were chosen, although some of them have moved in the ranking afterwards.

We should mention that to be able to include in the study cryptocurrencies that were relevant for their market capitalization in 2018, we chose July 2017 as the date for the beginning of the study. Specifically, as can be observed in coinmarketcap.com, where the data has been taken from, EOS has been listed from 1 July and Bitcoin Cash, one of the largest cryptocurrencies, from July, 2017. February 2018 was chosen to finalize the study, to include both the strongly bullish market during the second half of 2017 and the major crisis at the end of the year and the beginning of 2018.

Table 1 shows the different cryptocurrencies selected for the study, along with their coding and their volume as of 23 July 2017, measured in dollars.
Table 1. Cryptocurrencies selected for the study and their volume at 23 July 2017, measured in dollars

<table>
<thead>
<tr>
<th>NAME</th>
<th>CODE</th>
<th>VOLUME</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bitcoin</td>
<td>BTC</td>
<td>1,072,840,000</td>
</tr>
<tr>
<td>Ethereum</td>
<td>ETH</td>
<td>649,614,976</td>
</tr>
<tr>
<td>Ripple</td>
<td>XRP</td>
<td>195,682,000</td>
</tr>
<tr>
<td>Dash</td>
<td>DASH</td>
<td>31,110,400</td>
</tr>
<tr>
<td>Neo</td>
<td>NEO</td>
<td>29,915,100</td>
</tr>
<tr>
<td>Lisk</td>
<td>LSK</td>
<td>4,576,990</td>
</tr>
<tr>
<td>Stellar</td>
<td>XLM</td>
<td>10,264,600</td>
</tr>
<tr>
<td>Eos</td>
<td>EOS</td>
<td>60,205,000</td>
</tr>
<tr>
<td>Litecoin</td>
<td>LTC</td>
<td>219,256,992</td>
</tr>
<tr>
<td>Nem</td>
<td>XEM</td>
<td>5,915,450</td>
</tr>
<tr>
<td>Monero</td>
<td>XMR</td>
<td>8,634,060</td>
</tr>
<tr>
<td>Ethereum-classic</td>
<td>ETC</td>
<td>76,647,400</td>
</tr>
<tr>
<td>Bitcoin-cash</td>
<td>BCH</td>
<td>85,013</td>
</tr>
<tr>
<td>Omisego</td>
<td>OMG</td>
<td>15.198.100</td>
</tr>
<tr>
<td>Iota</td>
<td>IOTA</td>
<td>3.065.860</td>
</tr>
<tr>
<td>Bitconnect</td>
<td>BCC</td>
<td>2.132.900</td>
</tr>
</tbody>
</table>

Source: Coinmarketcaps.

For the study, daily prices at the close of trading have been taken from 23 July, 2017 to 16 February, 2018, which involves a total of 209 observations for each of the cryptocurrencies.

Figure 1 shows price fluctuations for the selected currencies during the whole period. As can be seen, it was the Bitcoin currency followed by Bitcoin Cash that reached the highest prices.

For the study of correlations, the daily rate of return was calculated for each of the currencies, defined as $r_i(t) = \ln P_i(t) - \ln P_i(t - 1)$ where $P_i(t)$ and $P_i(t - 1)$ are the prices of the cryptocurrencies at $t$ and $t - 1$, respectively.

Table 2 shows the statistical summary of returns on each of the currencies. As can be seen in this table, the average daily yield was negative, lower in the case of the BBC, and very low, in the case of losses standing at between -0.38% and -1.46%. Once again, except for the BCC case, which had a maximum daily yield of 258.6%, the maximum yield obtained by the other currencies was between 20% and 44.6%, while the losses, in this case for all the currencies taken together, stood between 22.5% and 99.6%, always with negative values. The scatter of signs in the relatively high asymmetry coefficients shows that the distributions were not symmetrical but rather both to the right and left. Finally, the kurtosis of the distributions of daily returns differed between the currencies studied.
Figure 1. Changes in daily cryptocurrency prices between 23/07/2017 and 16/02/2018

Source: Coinmarketcaps and in-house.

Table 2. Statistical summary of the return on the different cryptocurrencies (n=209)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Standard Deviation</th>
<th>Asymmetry Coeff.</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>BTC</td>
<td>-0.0064</td>
<td>0.2075</td>
<td>-0.2251</td>
<td>0.0599</td>
<td>0.1698</td>
<td>1.7324</td>
</tr>
<tr>
<td>ETH</td>
<td>-0.0069</td>
<td>0.2589</td>
<td>-0.2347</td>
<td>0.0641</td>
<td>0.3826</td>
<td>2.7059</td>
</tr>
<tr>
<td>XRP</td>
<td>-0.0085</td>
<td>0.3533</td>
<td>-0.6069</td>
<td>0.1014</td>
<td>-1.6264</td>
<td>9.5210</td>
</tr>
<tr>
<td>DASH</td>
<td>-0.0062</td>
<td>0.2432</td>
<td>-0.4377</td>
<td>0.0795</td>
<td>-0.7807</td>
<td>5.4611</td>
</tr>
<tr>
<td>LTC</td>
<td>-0.0079</td>
<td>0.3952</td>
<td>-0.3893</td>
<td>0.0854</td>
<td>-0.5673</td>
<td>5.4396</td>
</tr>
<tr>
<td>XEM</td>
<td>-0.0059</td>
<td>0.3615</td>
<td>-0.9956</td>
<td>0.1163</td>
<td>-2.9326</td>
<td>26.0569</td>
</tr>
<tr>
<td>XMR</td>
<td>-0.0093</td>
<td>0.2932</td>
<td>-0.3524</td>
<td>0.0861</td>
<td>-0.2041</td>
<td>2.1900</td>
</tr>
<tr>
<td>ETC</td>
<td>-0.0038</td>
<td>0.4353</td>
<td>-0.2923</td>
<td>0.0929</td>
<td>0.6827</td>
<td>4.6021</td>
</tr>
<tr>
<td>NEO</td>
<td>-0.0130</td>
<td>0.3285</td>
<td>-0.5089</td>
<td>0.1095</td>
<td>-0.7106</td>
<td>2.9434</td>
</tr>
<tr>
<td>LSK</td>
<td>-0.0131</td>
<td>0.4100</td>
<td>-0.3492</td>
<td>0.1019</td>
<td>0.0252</td>
<td>1.8135</td>
</tr>
<tr>
<td>XLM</td>
<td>-0.0146</td>
<td>0.3283</td>
<td>-0.6668</td>
<td>0.1225</td>
<td>-0.9675</td>
<td>4.3752</td>
</tr>
<tr>
<td>EOS</td>
<td>-0.0081</td>
<td>0.3850</td>
<td>-0.3473</td>
<td>0.1042</td>
<td>-0.1848</td>
<td>2.0175</td>
</tr>
<tr>
<td>BCH</td>
<td>-0.0064</td>
<td>0.4460</td>
<td>-0.4316</td>
<td>0.1212</td>
<td>-0.4931</td>
<td>2.7220</td>
</tr>
<tr>
<td>OMG</td>
<td>-0.0119</td>
<td>0.2846</td>
<td>-0.5416</td>
<td>0.1091</td>
<td>-0.6080</td>
<td>3.1269</td>
</tr>
<tr>
<td>IOTA</td>
<td>-0.0099</td>
<td>0.3770</td>
<td>-0.3840</td>
<td>0.1054</td>
<td>-0.2215</td>
<td>1.9610</td>
</tr>
<tr>
<td>BCC</td>
<td>0.0129</td>
<td>2.5864</td>
<td>-0.5925</td>
<td>0.2175</td>
<td>8.1337</td>
<td>96.0289</td>
</tr>
</tbody>
</table>
A visual summary of the above is shown in Figure 2, using a boxplot, showing that the median of the data for all the coins was close to zero. But perhaps what stands out most is the amount of extreme values that appear in all currencies, both positive and negative, thus reflecting the possibility of obtaining extreme gains or losses.

Figure 2. Box diagram of the returns on cryptocurrencies

3. Methodology of analysis

The first step for constructing the “Minimum Spanning Tree” (MST) is to calculate the matrix of correlations between the daily returns of all the cryptocurrencies studied, obtaining the coefficients of the Pearson correlations between each two currencies $i$ and $j$, defined as:

$$C_{ij} = \frac{n(\sum r_i r_j) - (\sum r_i)(\sum r_j)}{\sqrt{n(\sum r_i^2) - (\sum r_i)^2} \sqrt{n(\sum r_j^2) - (\sum r_j)^2}}$$

A correlation matrix is obtained:

$$C = \begin{bmatrix}
C_{11} & \cdots & C_{1N} \\
\vdots & \ddots & \vdots \\
C_{N1} & \cdots & C_{NN}
\end{bmatrix}$$

$C_{ij}$ takes values between -1 and 1, and $N$ is the number of currencies under study, which in our case is 16. According to Mantegna (1999) the elements of the correlation matrix $C_{ij}$, can be converted, transforming them into distances and obtaining a distance matrix where
\[ d_{ij} = \sqrt{2(1 - C_{ij})} \]

so that the value of \( d_{ij} \) may vary from 0 to 2, so if the distance is short, the correlation is high and vice versa.

To construct the MTS, N nodes, that in our case are the currencies to be studied, join up with \( N - 1 \) links, so that the sum of all the distances of the links is minimal. In practice this means that through the \( N - 1 \) links the most relevant information will be extracted from the correlation matrix. We have followed Mantegna (1999) and Mantegna and Stanley (2000) to produce the MST that propose the use of the Kruskal algorithm (1956). This can be summarized in the following steps.

(i) We took \( N(N - 1)/2 \) elements from the distance matrix in increasing order.
(ii) We selected the cryptocurrency pair with the shortest distance and added the link to the graph.
(iii) We selected the next pair of cryptocurrencies with least distance between them and added the next link.
(iv) We repeated (iii) until all the currencies were linked together in the figure.

4. Results

4.1. Correlations between cryptocurrencies

Before showing the MST obtained by means of the algorithm explained above, we compared the statistical descriptors of the \( N(N - 1)/2 \) elements of the correlation matrix obtained. This matrix was represented graphically in Figure 3. As can be seen, all the correlations were positive, ranging from a maximum value of 0.7 to a minimum value of 0.1, although their average value was 0.4, which implies that there was a moderate correlation between all of them. In addition, the significance of the values of the correlation coefficients was contrasted.
4.2. Results of the network

Figure 4 shows the MST for the 16 cryptocurrencies studied. Figure 4a illustrates the network structure of the crypto currencies, while figure 4b represents the same MST, however in this case the length of the link shows the relative distance between each two currencies depending on their correlation, so that the closer the two nodes, the greater the correlation between them.

It was observed that the most central currency was ETH (Ethereum), with more connections than any other and acting in turn as a connector between the other currencies. It is surprising that the most popular cryptocurrency, BTC (Bitcoin), did not appear as central, however its best-known rival, ETH (Ethereum) did so. Around the Ethereum, as a core, 4 groups of cryptocurrencies took shape, while others were linked in a dependent but isolated manner. This model, centralized in Ethereum, can be explained by both the growth in its quotation (in 2017, with more than a 4000%
revaluation. Thus Ethereum became the cryptocurrency with the second highest capitalization in the world) and also due to the nature of ICOs (Initial Coin Offering), since the vast majority do not display their own code but use the Ethereum platform. This creates a link between this currency and a large majority of cryptocurrencies that place it in the central zone, unlike the case of Bitcoin, which does not have this connection operational nor in the topological network.

Observing Figure 4b, it can be seen that the central currency is relatively close, which implies a high correlation with the majority of the currencies that it is directly connected with, with the exception of OMG (OmiseGo) and XMR (Monero). This can be explained by the specific nature of these two cryptocurrencies, making them different from the rest. Specifically, Monero does not use the standard protocol of the Bitcoin Blockchain but rather the CryptoNote protocol, focused on absolute privacy. This would lead us to suspect that it is highly biased towards opaque activities. For its part, OmiseGo aims to act not so much as a means of payment but rather as a decentralized online exchange platform, as opposed to the current centralized platforms, thus becoming a financial alternative.

Figure 4. (a) MST obtained from the matrix of correlations between all matrices, showing the relationship between the 16 cryptocurrencies studied; and Figure 4 (b) MST obtained from the matrix of the correlations between all matrices, which shows the relationship between the 16 cryptocurrencies studied. The shorter the distance between two nodes, the greater the correlation between them.
Classification of currencies into clusters through hierarchical analysis, by representing the dendrogram shown in figure 5. For its calculation, the method known as “simple” or “nearest neighbour” was used, as this is the one that is most closely related to the calculation of the MST. This method is based on forming an ascending cluster (agglomerative grouping) combining the groups that contain the closest pair of elements that do not belong to the same cluster. In this type of graph, the greater the difference in height, the greater the dissimilarity. Observing the graph it can be concluded that if a grouping in 7 clusters\(^1\) is chosen, each one represented by a colour, group 6 would contain 10 currencies within the same cluster. In addition, the short distance on the axis between the first clusters indicates the existence of little heterogeneity between the proposed groups, however the distance between the closest ETH (Ethereum) currencies and LTC (Litecoin), also joined by ETC (Ethereum classic) showed differential behaviour for this group.

Note that with the two methodologies used, MST and dendrogram, the most popular cryptocurrency does not appear as the most central in the study. This may be because Bitcoin is just a form of payment, which in actual fact has been exchanged on a major scale for speculative purposes, whereas Ethereum, as we have already explained, is a broader-based business project.

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(1) Seven clusters to separate the behaviour of BTC (Bitcoin), the most popular currency among the other cryptocurrencies studied.
Conclusions

This study shows that the use of hierarchical methods is useful to analyze the joint behaviour of the different cryptocurrencies. In particular, the structure of the correlation between 16 different cryptocurrencies was researched by constructing a complex network. Using daily price data between July 2017 and September 2018, the MST (Minimum Spanning Tree) was developed, placing the ETH cryptocurrency (Ethereum) in a central position in the network obtained from the correlations, leaving BTC (Bitcoin) in one of the branches of the network. In addition, the cluster analysis through the construction of the dendrogram reaffirms this conclusion and places Bitcoin in a different cluster from the one obtained with 10 other currencies.

The results obtained through this analysis constitute the first approach not taken prior to the analysis of the behaviour of cryptocurrencies through network analysis using Pearson correlations. The network obtained is a useful tool to be able to grasp the interrelationships between the financial assets that appear in it. The results obtained in the analysis could be of help to investors when making decisions about their portfolios, especially if we bear in mind that the correlation between financial assets is the basis of the theory of portfolio optimization.
References


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