RESEARCH

Analysis of the cryptocurrency market applying different prototype-based clustering techniques

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Abstract

Since the appearance of Bitcoin, cryptocurrencies have experienced enormous growth not only in terms of capitalization but also in number. As a result, the cryptocurrency market can be an attractive arena for investors as it offers many possibilities, but a difficult one to understand as well. In this work, we aim to summarize and segment the whole cryptocurrency market in 2018 with the help of data analysis tools. We will use three different partitional clustering algorithms each of them using a different representation for cryptocurrencies, namely: yearly mean and standard deviation of the returns, distribution of returns, and time series of returns. Since each representation will provide a different and complementary perspective of the market, we will also explore the combination of the three clustering results to obtain a fine-grained analysis of the main trends of the market. Finally, we will analyse the association of the clustering results with other descriptive features of the cryptocurrencies, including the age, technological attributes, and financial ratios derived from them. This will help to enhance the profiling of the clusters with additional insights. As a result, this work offers a description of the market and a methodology that can be reproduced by investors that want to understand the main trends on the market and that look for cryptocurrencies with different financial performance.

Second part title: Text for this section.

Keywords: Fintech; Data Sciences; Cryptocurrency; Electronic market

Content

The cryptocurrency market consists of more than 4,000 cryptocoins[1] with over 800 trades per second and more than 280 exchanges. It has become a huge new market in a very short term, considering that *Bitcoin* (Nakamoto (2009)), first peer-to-peer and decentralised digital currency was created in 2008 and the first bitcoin was mined in 2009. While cryptocurrencies were originally intended to enable anonymous wire transfers and online purchases, they have become a powerful investment tool.

However, this new market is very diverse. Crytocurrencies with different technologies, purposes, user base coexist and form a highly heterogeneous market that is difficult to understand and to manage for those addressing a good investment allocation.

[1]Although cryptoasset is a more general term, as explained in Burniske and Tatar (2017), we will use cryptoasset, cryptocoin and cryptocurrencies terms indistinguishably in this work.

As other assets, the value of cryptocurrencies swing based on news events, but cryptocurrencies have no physical assets or governments to back their value. Moreover, the cryptocurrency market is new, based on a still developing technology, highly speculative and small in comparison to others. As a result, it is highly volatile with big upswings, bubbles, and sudden market downturns.

Being a market so novel, big, diverse and volatile, it needs to be understood. Several categorization efforts have been made so far. For example, the *Cryptocompare* website [2] analyzed over 200 cryptoassets according to regulatory aspects, level of decentralization, supply issuance, economic incentive and others. Such taxonomy is useful even if it only covers approximately the 5% of the existing cryptocurrencies at that time. Another example is in Burniske and Tatar (2017) where classify over 200 cryptocurrencies into three classes of assets based on traditional financial markets, namely: capital asset, consumable/transformable assets and store of value asset. However, this classification is highly subjective as many times the cryptocurrencies may be a combination of some of them. Furthermore, these approaches typically cover a small fraction of the cryptocurrencies, which are the most important ones in terms of volume and popularity, and focus on qualitative aspects or aspects that do not change much.

A different approach consists of analysing the financial performance of the cryptocurrencies and describing it from a statistical point of view. In Chan et al. (2017) analyses a few cryptocoins (Bitcoin, Dash, Dogecoin, Litecoin, MaidSafeCoin, Monero and Ripple) which exhibit heavy-tailed distributions that fits the generalized hyperbolic distributions. In Hu et al. (2019) analyses the stylized facts and return properties of 222 cryptocurrencies and find a large degree of skewness and volatility in the population of returns. Furthermore, according to Pele et al. (2020) cryptocurrencies can be clearly separated from classical assets, mainly due to their tail behaviour. However, their cluster results also reveal that the behaviour of the cryptocurrencies is diverse.

The same conclusion can be drawn in other clustering analysis using cryptocurrencies. In Stosic et al. (2018) is represented the correlations of 119 cryptocurrencymarket as a complex network and discover distinct community structures in its minimum spanning tree. In Song et al. (2019) analyses 76 cryptocurrencies using the correlation-based clustering and filtering out the linear influences of Bitcoin and Ethereum and detect 6 clusters, but that do not remain stable after the announcement of regulations from various countries. The time dimension plays an important role in the work in Sigaki et al. (2019), that cluster the time series of 437 cryptocurrencies using hierarchical clustering and detect 4 different groups where the behaviour evolves differently in terms of efficiency for the information.

All these approaches reveal that it is possible to establish different groups of cryptocurrencies in terms of their financial performance. And identifying them, it is useful to better understand the cryptocurrency market, but also for building a diversified portfolio.

All of these methods use different representations of the cryptocurrencies: correlations in Song et al. (2019); Stosic et al. (2018), factors extracted from the correlation

[2] https://cryptocompare.com

matrix (Pele et al. (2020)) and time series (Sigaki et al. (2019)) . Each representation focuses on different aspects of the cryptocurrency that are meaningful for the purpose of the analysis.

However, it would be possible to combine the clustering results using different representations of the cryptocurrencies where each one take into account different aspects of the cryptocurrencies. In this way, the combination of the clustering results would make possible to characterize each cryptocurrency in several dimensions, one for each cluster strategy. If the clusters for each cluster strategy are meaningful, their combination would offer a more detailed characterization of the market and useful insights for portfolio management.

In this work, we will explore the combination of clustering of cryptocurrencies using R Core Team (2013). We will go beyond a few hundreds cryptocurrencies, as most studies do, and will explore all the cryptocurrencies traded in 2018 (more than 1,700 cryptocurrencies) easily scalable for a growing market. We will describe each cryptocurrency considering the log return transformation of the daily price in 2018 with three different levels of granularity:

- Mean and standard deviation of the daily returns
- Distribution of the daily returns
- Time-series of the daily returns

In the first case, we provide a meaningful summary commonly used to describe financial assets over time as it is the annualized return and volatility, or with the central tendency and the dispersion of the returns. In the second case, we consider the whole distribution of returns that accounts not only for the central tendency and dispersion of an asset, but for the whole aggregated behaviour including asymmetry, kurtosis and the tails. Methods to analyse distributional data belong to the field of symbolic data analysis (Noirhomme-Fraiture and Brito (2011)), where observations account for internal variation that can be represented as intervals or distributions, and have been previously used in finance (Arroyo and Maté (2009); Arroyo et al. (2011); González-Rivera and Arroyo (2012)). Finally, we consider the observed data, that is the log return time series that accounts for variations over time and makes possible to identify when volatile or stable periods take place in each cryptocurrency.

There is a high diversity of clustering techniques, but in our case the interest lies on the different perspectives shown at each level of granularity. Thus, for all the representations we will use a partitional prototype-based clustering algorithms with a similarity measure (distance) meaningful for each kind of representation. In this way, we will have a prototype describing the behaviour of each cluster using the same representation of the data. Prototypes make possible to assign a financial meaning to the whole cluster.

Then, we will combine the three clustering results and analyse the most numerous intersections with the help of visual tools. Such approaches are successfully used in biostatistics (Kern et al. (2017); L'Yi et al. (2015)). In our case, we will use them to represent the main trends in the cryptocurrency market. If several cryptocurrencies belong to the same clusters in the three clustering results then we can consider them as very similar. We will inspect the relationship among the three clustering results with the help of visualization tools.

This approach provides a screening mechanism that allows us a meaningful exploration of the whole market in spite of its complexity and size. The intersection of the clustering results can also be helpful for investors in order to select a suitable cryptocurrency for the portfolio as it characterizes the cryptocurrency market in more detail.

In a further step, we will investigate the association between the clustering results and different features of the cryptocurrencies such as technological variables, the market capitalization, the *maturity* (age) of the cryptocurrency, and some of asset portfolio ratios. We aim to inspect whether some clusters are tightly associated or not with some aspects not taken into account the clustering process. we apply some inference statistical tests to assess whether associations are significant. These associations enhance the profiling of the different clusters. We keep continuous references to concrete cryptocurrencies of the market, most of them no very known, that are part of our analysis. Finally, we present our conclusions with some points open to debate.

Related work

Clustering financial data

Clustering analysis is a well-known data analysis tool that have served well in different fields (Henning et al. (2016)). In particular in Finance, the seminal work of Mantegna (1999) used the cross-correlation of the return time series and Minimum Spanning Trees (MST) to group the stocks of the New York Stock Exchange from 1989 to 1995. In Mantegna (1999) is applied the MST to represent the stock market as a network. Later, in Bonanno et al. (2004) applies the same methodology considering different time horizons comparing the return and volatility networks. The methodology of Mantegna is applied with different variations in other contexts (Brida and Risso (2009); Mizuno et al. (2006); Onnela et al. (2003)). Furthermore, different alternatives and variants of this methodology have been proposed as it can be seen in the review in Marti et al. (2017)

Another strand of clustering applied partitional methods as we do but more specifically fuzzy-types to financial markets typically used for grouping stocks for developing portfolios. In Nanda et al. (2010) applies K-means, Fuzzy C-means and Self Organizing Maps (SOM) to returns and financial ratios from Indian stocks to classify them in different clusters and subsequently develop portfolios from these cluster. A derivate approach is shown in Chaudhuri and Ghosh (2015), who group the daily Indian market volatility comparing Kernel K-means, SOM and Gaussian clustering models to achieve right volatility prediction using the clusters as predictors. In the same way, Pierpaolo et al. (2013),D'Urso et al. (2016) and D'Urso et al. (2020) applied different variations of fuzzy clusters to financial markets. Our methodology requires fully distinguished classes for the clustering objects, partial membership of *fuzzy* clusters is more complicated to handle with our approach so a pure crisp partitions is preferred for the methodology proposed.

In Liao (2007); Liao and Chou (2013) do clustering on the daily market data and apply different association rules between the K-means groups, indices and market categories. That associations help to analyse and describe the co-movement among the different markets.

Regarding the use of time series as objects to cluster, in Aghabozorgi and Teh (2014) propose a three-phase clustering model to categorize companies based on the similarity in the shape of their stock markets using Dynamic Time Warping (DTW) (Berndt and Clifford (1994)).

From traditional finance to cryptoasset markets

In Yermack (2013) analyses Bitcoin market in-depth and considered it an investment more speculative than a currency.It is considered that it poses high risk for the management of transactions and credit markets. Finally, a deflationary scenario is anticipated because of the limited number of bitcoins that can be issued (21 millions). The paper anticipated many aspects of the cryptocurrency markets that we are experiencing today (excessive volatility, high level of computer knowledge required for using and integration into the web of international payments).

The high growth of the cryptocurrency market and its heterogeneity since 2014 was analysed in depth in Corbet et al. (2019) considering different aspects including regulatory, cyber-criminality, market efficiency or bubble dynamics and make recommendations for further investigations on different domains. We take a couple of them and we address in our work some characteristics based on liquidity (market cap) and other key market metrics, for instance, Beta or Modigliani-Modigliani financial ratios.

The characterization of the cryptocurrencies from a statistical point of view has been tackled by different works. In Chan et al. (2017) analyses the distributions for a few cryptocurrencies (Bitcoin, Dash, Dogecoin, Litecoin, MaidSafeCoin, Monero and Ripple) and show that they exhibit heavy-tailed distributions that fit the generalized hyperbolic distributions. As part of a benchmark with other markets, in Baek and Elbeck (2015) shows that the volatility of Bitcoin market shows that bitcoins are 26 times more volatile than S&P 500 Index.

In Zhang et al. (2018) analyses the stylized facts of eight cryptocurrencies that represent almost 70% of the market capitalization and find, among other things, heavy tails for the returns, return autocorrelations that decay quickly, while the autocorrelations for absolute returns decay slowly, that returns display strong volatility clustering and leverage effects, and a power-law correlation between price and volume. The study of stylized facts have been extended increasing the number of digital coins up to 222 Hu et al. (2019).

Clustering of cryptocurrencies

The classical methodology based on MST algorithms (Mantegna (1999)) is applied in Song et al. (2019) to filtering the influence of *Bitcoins* and *Ethereum* and detects six homogeneous clusters. However, the structure found does not remain stable after the announcement of regulations from various countries. Interestingly, the uses of clustering together with other methods, such as VAR models and Granger causality tests (Zieba et al. (2019)) help to find that Bitcoin shock prices are not transmitted to the prices of other cryptocurrencies, being *Litecoin* and *Dogecoin* the more influential actors. According to the results, Bitcoin exhibits a lower relationship with other cryptocurrencies. Other approach is the use of random matrix theory and hierarchical structures in a MST on 119 cryptocurrencies from 2016 to 2018 (Stosic et al. (2018)). It is showed that the presence of multiple collective behaviours in the market of cryptocurrencies, which contrast to the intuitive idea that Bitcoin exerts a global influence on the entire market.

Furthermore, the time dimension can also be taken into account evolve. In Sigaki et al. (2019) first classify 437 cryptocurrencies according to information efficiency using permutation entropy and statistical complexity, and then cluster their time series using dynamic time warping and hierarchical clustering to find four groups where the behaviour in terms of information efficiency evolves differently. All these articles evidence the complexity of the underlying structure in the cryptocurrency market, where some cryptocurrencies influence others even in unexpected ways.

The comparative study of cryptocurrency markets and traditional financial markets is also an essential domain of investigations. In Corbet et al. (2018) shows that cryptocurrencies are highly connected among themselves and disconnected from mainstream assets (bonds, stocks, S&P500, gold).In Pele et al. (2020) merge classification based on asset profiles and dynamic evolution of clusters. It starts with a characterization of selected group of log-returns assets including 150 cryptocurrencies, stocks commodities and exchange rates to estimate a multidimensional vector applying a dimension reduction (Factor analysis). Then, they use classification where K-means is one of the techniques applied. The main difference of Cryptocurrencies with respect to traditional assets is a higher variance and longer tails of the log-return's distribution. The work also shows that individual cryptocurrencies tend to develop over time similar characteristics (synchronic evolution).Drozdz et al. (2019)shows that the multiscaling characteristics of the exchange rate fluctuations comparing the cryptocurrency market approach to those of the Forex; furthermore Begusic et al. (2018) estimates the scaling exponent and find the asymptotic power-law behaviour for Bitcoin.

Methodology

Dataset preparation

We retrieved data from `https://www.cryptocompare.com/` for all the cryptocurrencies traded during 2018. New cryptocurrencies have appeared in the last years, but many of them were short-lived and barely traded. We aim to incorporate in our descriptive estudy as many cryptpcourrencies as possible on the market during the period which means that we are very conservative on the *clearing data* criteria, we only removed NaN and Inf observations mainly caused by zero-prices in log transformations. As result, from all the downloaded cryptocurrencies we filtered out those that were in the market less than the 95% of the days (92 cryptocurrencies in 2018), but we kept some that were in the market but were not traded, i.e. zero return and volatility or zero volume. Our final data set consists of 1,723 cryptocurrencies. Anyway, part of the cryptocurrencies present a very low activity in the market point to low liquidity that cause heavy-tails effect so for that case we apply a specific *filter* in some parts of the study, mainly for association tests

For these cryptocurrencies we constructed the following variables:

- **Daily log-returns**: The use of returns instead of prices in Finance price time-series is very extended and consolidated due to its more suitable statistical properties and better comparability. It has been used in cryptocurrency markets as well Letra (2016); Stosic et al. (2018). The return for the cryptocurrency i at day ts is computed as:

$$r_i(t) = ln(P_i(t)) - ln(P_i(t-1))$$

where $P_i(t)$ is the daily cryptocurrency price for i cryptoasset at day t.

- **Volume**: It is the daily traded volume in units of the base cryptocurrency that can be understood as a liquidity proxy. We transformed it into an ordinal variable by the quantile functions. Three cryptocurrencies represent 66% of the trading volume of the market in 2018, namely Bitcoin (46%), Ethereum (16.5%) and EOS (4%), and in total 10 cryptocurrencies (`BTC, ETH, EOS, BCH, XRP, LTC, ICX, HSR, ETC, IOT`) represent 80% of the daily volume.
- **Market cap**: it is the one-day market cap retrieved directly from the market on the 4th of February in 2019. Three cryptocurrencies represent 60% of the *market cap*, namely `WBTC*` (26.8%), `BTC`(22.4%) and `NPC` (11.5%), and in total 5 cryptocurrencies (`WBTC*, BTC, NPC, XRP, AMIS`) represent 80% of the *market cap*
- **Technological variables**: We represent the encryption and consensus algorithms of the cryptocurrency as nominal variables:
  - **Encryption**: There are 105 different values. The more relevant encryption algorithms are Scrypt, SHA256, SHA256D, X11, X13, X15, PoS, Multiple and CryptoNight. We notice that this information is not available for 35% of the cryptocurrencies (599 obs.).
  - **Consensus**: There are 60 possible values, including the well known Proof of work (PoW) and Proof of Stake (PoS). The most predominant are obviously PoW/PoS, PoW and PoS but this information is missing in 31% of the cryptocurrencies (536 obs.)
- **Age**: We estimate the time on the market of each cryptocurrency, and transform it into an ordinal variable by a quantile function. *Age* and *maturity* are interchangeable on our study.

Besides the cryptocurrency data, we also retrieve time-series from https://cci30.com/ which is a rules-based index designed to objectively measure the overall growth, daily and long-term movement of the blockchain sector and the US Department of the Treasury[3] that we use for the computation of some financial benchmarking rates as Beta, Sharpe ratio and others that we will explain in the next sections.

Volume of negotiation and tail distribution analysis

We aim to consider all cryptocurrencies that existed on the market independently of the transaction volume or liquidity. For sure liquidity or volume of trading is a key aspect to keep in mind to characterize the market but our first priority is to represent and manage all the market. We represent a histogram of non-trading days based on the volume negotiated (volume equal to zero means in our case no traded asset) on Figure 1 where 306 cryptocurrencies has been traded (volume of negotiation equal to zero) no day during 2018 (18 crypto currencies traded only 2 days). As we commented, we consider relevant to keep non-traded cryptocurrencies as part of our market analysis for the clustering part just to detect where they are allocated. However, we agree on the low interest for the investor in lower liquidity crypto assets.

[3] https://home.treasury.gov/

The concept of power-law distribution Newman (2005) and applications on cryptocurrency case Begusic et al. (2018), Watorek et al. (2020) is relevant to confirm the existence of 1st and 2nd order moments on our data to ensure the applicability and generalization of the results of clustering and the inference tests. The existence of the statistic moments according to the power-law Gillespie (2015) is:

$$p(x) = \frac{\alpha - 1}{x_{min}} \left(\frac{x}{x_{min}} \right)^{-\alpha}, \tag{1}$$

and for the CDF

$$P(X \leq x) = 1 - \left(\frac{x}{x_{min}} \right)^{-\alpha+1}, \tag{2}$$

The moments of the power law distribution for the continous power law are the following:

$$E\left[X^m\right] = \int_{x_{min}}^{\infty} x^m p(x) \cdot dx = \frac{\alpha - 1}{\alpha - 1 - m} x_{min}^m \tag{3}$$

Generally speaking when

- $1 \leq \alpha \leq 2$, all moments diverge, i.e., $E[X] = \infty$;
- $2 \leq \alpha \leq 3$, all second and higher-order moments diverge, i.e., $E[X^2] = \infty$;
- $3 \leq \alpha \leq m+1$, all m and higher-order moments diverge, i.e., $E[X^m] = \infty$;

Newman (2005) showed that for the case $2 \leq \alpha \leq 3$ as X_{max} becomes large we get that

$$E\left(x^2\right) \sim n^{(3-\alpha)/(\alpha-1)} \tag{4}$$

converge. In 14, 15, 16, 17 and 18 we have computed the maximum likelihood estimator (MLE) for the continous power law for the negative and positive tails on the variables `AlphaP` and `AlphaN` as follows:

$$\hat{\alpha} = 1 + n \left[\sum_{i=1}^{n} \log \frac{x_i}{x_{min}} \right]^{-1} \tag{5}$$

with the following expected statistical error (variables `Sd.P, Sd.N` for positive and negative tails on the table 14)

$$\sigma = \sqrt{n} \left[\sum_{i=1}^{n} \log \frac{x_i}{x_{min}} \right]^{-1} = \frac{\alpha - 1}{\sqrt{n}} \tag{6}$$

In our view, we consider that power-law behaviour could be more impacting on the generalization of the inference tests than clustering partitions. Our goal is to represent all the cryptocurrency market on a clustering maps independetly of any statistical property or behaviour considering them as objects and in that way we keep the 1723 cryptocurrencies for clustering.In other words, we want to know where are allocated the highest *heavy-tail* cryptocurrencies as well. For association tests our goal is the generalization of the results and in that way we filtered out the lsit of cryptocurrencies keeping only the higher statistic quality, 1262 cryptocurrencies in total.

Methods

We aim to find groups of cryptocurrencies based on the behaviour of their log-returns in 2018 and describe them. For such purpose we will use different clustering algorithms that will deal with the three representations of the log-returns described in the previous section: statistic moments, observed probability distribution and observed daily time-series.

We use centroid-based clustering algorithms because the centroids provide us an interpretable summary of the elements of each cluster, which will help us to identify the most relevant features of the cluster elements. A drawback in this type of clustering algorithms is that they assume knowledge about the desired number of clusters (k). We apply different quality criteria to determine the optimum number of clusters depending on the technique.

Moreover, we use distance-based clustering algorithms they are simple, intuitive and applicable for a wide variety of scenarios Aggarwal et al. (2013). The algorithms considered will be based on meaningful dissimilarity measures or distances that help on the interpretability of the clusters. That is especially important for more complex representations such as the distributions or the time series. For example, in the case of distributions, the measure should relate with properties of the density function (central tendency, spread, symmetry), while in the case of time series will be more with the shape of the time series along time. Meaningful measures will help us to understand better the resulting clusters and to interpret the nearness of the observations to the centroid. In addition, our clustering algorithm provide a prototype or a centroid of the clustering, which eases the characterization of the resulting clusters.

The cluster intersections help us to merge the results of the different clusters and identify the most prominent cryptocurrency profiles along 2018 according to different characteristics through the three techniques. Furthermore, we analyse the association between the clustering results found for the three representations and the different attributes of the cryptocurrencies.

The k-means clustering algorithm for the first and second statistical moments

For the bi-variate (or two-moments) representation, where the two variables are the yearly mean and standard deviation of the log-returns we use the k-means clustering MacQueen (1967), which is one of the most widely used clustering algorithms Wu et al. (2008). We standardize the two variables to homogenize the differences between their ranges. The K-means clustering minimizes within-cluster variances, that is, squared Euclidean distances inour case, which makes the result easy to understand and interpret. Before the clustering, we compute the Hopkins statistic Banerjee and Dave (2004) to rule out the possibility that a uniform random distribution generated the data set.

For the selection of the number of clusters (k) we compute several internal Cluster Validity Indices (CVIs) for crisp partitions Arbelaitz et al. (2013), including silhouette, Dunn, COP Davies-Bouldin, Calinski-Harabasz or the score function, and then apply the majority rule to choose the best number of clusters.

We apply clustering ensemble techniques Acharya (2011) aiming at reducing the randomness on the partitional cluster results. We run the K-means algorithms 10 times and we ensemble the outcomes minimizing the Euclidean distance. We confirm that the dissimilarity among the different runs is closer to zero, which makes the ensemble cluster a more stable representation. For each algorithm run, we apply the Hartigan-Wong method for clustering Hartigan and Wong (1979) with ten iterations to reach convergence and considering 50 random starts for each iteration. Once we have the 10 algorithm runs, we compute the medoid of an ensemble of partitions, i.e, the element of the ensemble minimizing the sum of dissimilarities to all other elements Hornik (2005, 2019).

The dynamic histogram clustering for the log-return distribution

For the yearly log-return distribution, we apply a clustering algorithm that deals with histogram-data form. More precisely, we apply the dynamic clustering algorithm for histogram data based on the l_2 Wasserstein distance Irpino and Verde (2006); Irpino et al. (2014). In this way, we will group the cryptocurrencies with similar distributions of log-returns in 2018.

The dynamic clustering algorithm needs a dissimilarity function to assign the observations to the clusters, which is the l_2 Wasserstein distance. Given two histograms h_1 and h_2, the l_2 Wasserstein distance is defined as

$$d_W(h_1, h_2) := \sqrt{\int_0^1 \left[F_1^{-1}(t) - F_2^{-1}(t)\right]^2 dt} \tag{7}$$

where F_1^{-1} and F_2^{-1} are the inverse of the cumulative distribution functions, that's the quantile functions of h_1 and h_2, respectively. This distance can be decomposed as follows:

$$d_W(h_1, h_2) = \sqrt{(\mu_1 - \mu_2)^2 + (\sigma_1 - \sigma_2)^2 + 2\sigma_1\sigma_2\,(1 - \rho_{1,2})} \tag{8}$$

where μ_i and σ_i are respectively the mean and the standard deviation of the h_i and $\rho_{1,2}$ is the correlation of h_1 and h_2 Irpino and Verde (2015). As a result, the l_2 Wasserstein distance can be decomposed in the addition of three elements that account for the histogram differences in terms of location, spread and shape, respectively. Interestingly, this distance matches the perceptual similarity that the human observes when comparing distributions Arroyo and Maté (2009). All these aspects make it a suitable distance for clustering distributions and, in our case, log-return distributions.

The Dynamic Clustering Algorithm for histogram data based on the Wasserstein distance (Hist DAWass) is a k-means-like algorithm for clustering a set of observations described by histogram variables Irpino and Verde (2006); Irpino et al. (2014).

Each of the k clusters is represented by a centroid or prototype and observations are assigned to the closest prototype. The prototype is the average histogram of the observed histograms for each variable. In our case, observations are described by a single histogram variable representing the distribution of log-returns and the resulting prototype is a histogram that averages the histograms of the observations that belong to the cluster Irpino and Verde (2015). As a result, the prototypes can be interpreted in a financial context as log-return distributions.

We use the clustering implementation in the R-package HistDAWass Irpino (2016). This implementation provides quality measure that is the percentage of Sum of Squared (SS) deviation explained by the model running the algorithm several times for each k. We run the clustering algorithm 20 times for each k and the solution is the best one among the repetitions, that is, the one that maximizes the SS.

The TADPole clustering for the log-return time-series

Time-series clustering is a challenging domain for clustering due to the high dimensionality of the objects and how they are ordered. As a result, many approaches have bee proposed over time Aghabozorgi et al. (2015); Liao (2005); Rani and Sikka (2012).

We wish to cluster the time-series with similar volatility patterns in the same periods. For this purpose, Euclidean distance may fail to produce an intuitively correct measure of similarity between two time series, because it is very sensitive to small distortions in the time axis. However, other measures, such as Dynamic Time Warping (DTW), cope with this problem by *warping* non-linearly the time dimension to estimate their similarity. Nowadays, DTW is considered one of the most popular and useful shape-based measures Aghabozorgi et al. (2015).

However, DTW is intrinsically slow because of its quadratic time complexity, which hampers its applicability in clustering. Thus, we use the TADPole (Time-series Anytime Density Peak) Begum et al. (2015) clustering algorithm that extends the Density Peak (DP) clustering framework Rodriguez and Laio (2014) and exploits the upper and lower bounds of DTW to prune unnecessary distance computations which speed-up the convergence of the algorithm. As a result, TADPole produces a right answer quickly, and then refines it until it converges to the exact answer. Besides, the clustering algorithm only needs two parameters which makes it easy to use. Firstly a cut-off distance that define the thresholds to select the series and we set it to 2; and secondly, a windows-size that define the time frame to make the comparison between the series that we set to 3. Optionally we can also select the number of clusters (k) or we can let the algorithm to choose the optimal one based on the local density of points (closer series at some time based on some cut-off distance) using a "knee point finding" algorithm where points with higher values of $\rho_i \cdot \delta_i$, where ρ_i referred to the local density and δ_i is the distance from points with higher local density.

We will consider a different number of clusters k and compute the internal Cluster Validity Index (CVI) for each of them. As this clustering algorithm uses three distances, we used as CVI the Calinski-Harabasz index that secure the convergence of the algorithm for asymmetric distance measure.

TADPole allows to cluster time-series with arbitrary shapes which is very useful in our case because of the heterogeneity of the cryptocurrency market. In contrast, TADPole clusters cannot be represented as "balls" in a metric plane as in K-means for example. The result is a Partition Around Medoid (PAM) type centroid using the DTW distance that can be represented in a DTW space. This centroid is a time-series that serves us to identify the volatility patterns of the resulting clusters.

We apply the R implementation of TADPole algorithm in the R-libraries Sarda-Espinosa (2019); Sardá-Espinosa (2019). The time series is on log-return values which facilitate the characterization of the clusters. The DTW measure implemented in the package follows the estimation by Lemire (2008).

Combination of clustering results

Once we have the results of the clustering algorithms, we combine them by intersecting the clusters. Potentially we have $T_1 x T_2 x T_3$ intersections where T_n is the number of clusters that we obtain with the clustering algorithm n. The combination of the clustering results would make possible to characterize each cryptocurrency in several dimensions, one for each cluster strategy. The resulting multi-dimensional categorical datasets can be shown using visualization techniques supported on the graph theory Kern et al. (2017); L'Yi et al. (2015). To better highlight the changes in the clustering between the different techniques, we have visualized such changes by means of a so called alluvial diagram Rosvall and Bergstrom (2010). We use the alluvial visualization implemented in R-library Bojanowski and Edwards (2016) to show the main *flows* of cryptocurrencies.

We will analyse the clustering intersections with the higher cardinality to better profile the main trends of the cryptocurrency market.

Association test

Finally, we complement the information of each cluster result by studying the level of association with different independent variables not considered in the clustering process. We analyze the association among clusters and the categorical variables defined in Table 1 by applying the exact Fisher's tests and analysing the Person's residuals of the contingency tables that we explain later. Firstly, we transform quantitative variables into ordinal by applying the quantile functions.

We introduce below some variables that are financial ratios Bacon (2008) that we borrow from portfolio theory and we use to characterize the behaviour of the cryptocurrencies from a investor perspective, enhancing the association study as well. The computation of most of the below ratios (except Beta that has been manually computed) rely on the ratios implemented on R-library Peterson et al. (2018).

Beta is a volatility measure of systematic risk of an asset, the risk inherent to the entire market that is non-diversifiable, in statistic terms, *beta* is the slope of the regression of our asset compared with a reference on the market:

$$\beta = \frac{Cov(R_c, R_b)}{Var(R_b)}, \tag{9}$$

where R_c is the return of our cryptocurrency, R_b is the return of the bench market, the CCI30 index that track the 30 largest cryptocurrencies by market capitalization, excluding stablecoins. . The *beta* value shows whether an asset moves in the same direction as the reference index, and how volatile or risky is compared with it. The Beta for the whole market is 1.0. A positive beta means the asset moves in the same direction as the market, while negative beta means that the asset moves in opposite direction. Furthermore, an absolute value greater than 1 means greater sensitivity to systematic risk, i.e. higher risk; while values lower than 1 mean less sensitivity.

The **Sharpe ratio**(Sharpe variable) is the exceed average return of risk-free by volatility unit or total risk. The ratio determines the risk of the investment with respect to the return of an investment with zero-risk:

$$SR_c = \frac{E[R_c - R_f]}{\sigma_c}, \tag{10}$$

where R_c is the return of our cryptocurrency, σ_c is standard deviation or the volatility of our cryptocurrency and R_f is the *risk-free* rate taken as reference; we considered the daily of the annualized T-Bill over 90 days, and its daily value for 2018 was $E[R_f] = 0,005254377\%$. The greater the value of the Sharpe ratio, the more attractive the risk-adjusted return of the cryptocurrency.

Typically, **Chi-Square test** is used to examine the significance of the association between categorical data on a contingency table. However,the significance value is an approximation that it is not adequate when the sample size is small. We ruled out the Chi-Square test since results are not significant if the expected frequency is not typically higher than 5 in at least 80% of the cells of the contingency table (Yates (1984)) and this assumption is not fulfilled in our case for many of the categorical variables for some levels. we will use the Fisher's exact test (Fisher (1922)) to test the association between the variables of the Table 1 and the cluster results, which is applicable for all sample sizes. This test assumes no dependency between the categorical variables as null hypothesis, and assumes a multivariate hyper-geometric distribution for the cells into the contingency tables (Mehta and Patel (1983)).

For large datasets Monte Carlo method provides an unbiased estimate of the exact *p-value* (Mehta and Patel (1996)). Monte Carlo is a repeated sampling method that for any observed table, there are many tables, each with the same dimensions and columns and row margins as the observed table. Monte Carlo simulations are implemented in R stats-package for the *chisq.test* function. We run 8,000 simulations for each association, i.e. for each pair of variables under analysis, generating simulated contingency tables filled with a sampling of a multivariate hyper-geometric distribution. Then we compute the probability that we have a distribution as we effectively have observed, that is the *p-value*. A cell-by-cell comparison of observed and estimated frequencies evidences the nature of the dependence. If the p-values of the Fisher association tests between a couple of variables is lower than 0.01 then we consider that the association is significant. For each significant association between categorical variables of the contingency table we analyse standardized (adjusted) Person's residuals for the cell ij (Agresti (2018)), which is defined as follows

$$r_{(Adj)ij} = \frac{O_{ij} - E_{ij}}{\sqrt{E_{ij}(1 - \frac{m_i}{N})(1 - \frac{n_j}{N})}} \tag{11}$$

where O_{ij} and E_{ij} are the observed and expected frequency, respectively, m_i is the row total, n_j is the column total, and N is the total number of observations.

The sign of the residual (positive or negative) indicates whether the observed frequency in cell ij is higher or lower, respectively, than the value fitted under the model, while the magnitude indicates the degree of departure. A standardized residual having an absolute value that exceeds about 2 when there a few cells, or about 3 when there are many cells indicates that the cell do not satisfy H_0 (Agresti (2018)). In our case, we assume a more conservative position and we consider as a cut-off for significant standardized residuals those that exceed 3.5.

We will use association plots to indicate deviations from a specified independence model of our contingency table. The association plots provide a quick means for visualizing the residuals of an independence model for a contingency table(Meyer et al. (2006, 2020); Zeileis et al. (2007)). In the association plot, each cell is represented by a rectangle that has (signed) height proportional to $r_{(Adj)ij}$ and width proportional to $\sqrt{E_{ij}}$, so the area of the box is proportional to the difference in observed and expected frequencies. The rectangles in each row are positioned relative to a baseline indicating independence ($r_{(Adj)ij} = 0$). If the observed frequency of a cell is greater than the expected one, the box rises above the baseline, and falls below otherwise. Additionally, the residuals can be coloured depending on a specified shading scheme. In our case, blue tones for positive residuals and red tones for negative ones, darker tones will be associated for the higher residual absolute values.

Results

In this section we present the results of the three clustering algorithms, of the intersection clustering and finally of the association tests. In Table 2 we summarize the three clustering results, showing for each cluster its cardinality and, for the sake of comparison, the observed mean and standard deviation of the prototypes (for the K-means we show the centroid values).

Clustering results of the bi-dimensional (one-two moments) representations

For the existence of clusters, the Hopkins statistic computed on scaled average returns and volatility is 0.01552. The value is below 0.5 which points out the existence of an underlying structure.

The optimum number of clusters according to the CVI indexes is three. The descriptive statistics of the three centroids in ordinary values are shown in Table 2 and Figure 2(a) shows the scatter plot with the clusters.

The algorithm clearly discriminate the cryptocurrencies between lower (Clusters 2 and 3) and higher volatility (Cluster 1) which is the less populated cluster as well. From a financial perspective, Cluster 1 includes the riskier cryptocurrencies. The cryptocurrencies of Cluster 3 mostly have negative mean returns, while those in Cluster 2 have higher returns, some of them positive and others negative. In general, the three centroids are close to the zero mean return point.

Figures 3(a), 4 and 5 show a more detailed view of each cluster. In these figures we represent in a contour plots the density in the bi-dimensional (two-moments) space $(\bar{r}, \sigma)$ that help us to locate the areas where cryptocurrencies tend to be more concentrated.

- **Cluster 1**: This cluster allocate cryptocurrencies with negative average returns, but with very high volatility, ranging from 1 to 5. It includes only 19 cryptocurrencies that represent around 1% of the sample as we see in Fig. 3(a). The higher concentration of cryptocoins into this cluster is surrounding volatility 1.5 and mean return around -0.1 as we see in Fig. 3(b). `ELTCOIN` (token that run on Ethereum blockchain network released in October 2017) has a central position in the cluster and around it we can find `B2X`, `ADCN` (no traded on the market since November 2019), `BLX`, `WAND` (derivative market platform), `GOOD`, `SBIT`, `ZCG`, `ITT`, `REX`, `STAR` (it is a token and operates on the Ethereum platform, higher volume in Ethereum along 1st and last quarter of 2018) and `PFR`. We see into this cluster a mix of Ethereum tokens and cryptocoins with its own blockchain, most of them with low traded volume which may cause that a few operations trigger the volatility.
- **Cluster 2**: This cluster is the more populated with around 900 cryptocurrencies (52% of the total). It allocates the *moderate* behaviours including the higher mean return cryptoassets. It is also less homogeneous than the others, with different dense areas of concentration as we see in Fig. 4(a)) which point out the existence of other cluster. Most of the high capitalization cryptocurrencies (`BTC`, `EOS`, `ETC`, `ETH` or `LTC`) are in the sub-cluster with very low volatility and moderate negative return shown in Fig. 4(b). However, we can also find some cryptocurrencies with moderate positive returns (134 cryptocurrencies) and very low volatility, as shown in Fig. 4(c). These cryptocurrencies include `ALEX` (low trading in the first half of 2018 and higher activity in the second half of 2018), `BST` (BlockStamp had very low activity along 2018), `ETL` (EtherLite is a ERC20 token based on Ethereum with high peaks of activities in the first quarter of 2018 and no activity in the remaining part of the year) or `OPES` (OpesCoin had a moderate activity in the first half of 2018, and was flat in the second); all of them can be considered low-medium market capitalization (under 70^{th} percentile). In Cluster 3, it is also possible to find a few cryptocurrencies with higher returns, but they have a low market capitalization.
- **Cluster 3**: This cluster has 801 cryptocurrencies, most of them with negative average returns, and volatility lower than 0.5. According to Figure 5(a), the highest concentration of cryptocurrencies is located in mean return closer to zero and volatility around 0.1. Some of the more representative cryptocurrencies of this cluster in terms of market capitalization are XEM, VIA, QRL, DASH, QTUM, XST and BCH that are close in the cluster (see Figure 5(b)).

We confirm that the K-means clustering identifies three different behaviours on the cryptocurrencies in terms of mean returns and volatility.

Clustering results of log-return histogram representations

According to the CVI, the clustering algorithm for histogram data based on l_2 Wasserstein metric Irpino (2019) separates the cryptocurrencies into five clusters. Each cluster is represented by its prototype, which is a log-return distribution. Table 3 shows the descriptive statistics from the prototypes of the five clusters.

The five distributions exhibit a slightly negative central tendency measures, being Cluster 1 the one with the lowest values. They are quite symmetrical, with low skewness and heavy tails pointed out by a high kurtosis. Skewness is closer to zero in all cases but it is positive, which means that the right tail of the distribution is fatter, or in other words, it has more extreme positive return values (or over the mean) on the right.

It is important to remark that the coefficient of variation for the centroids is quite different in all the clusters ranging from -0.75 to -32.90, which point out that this clustering algorithm is specially sensitive to this particular statistic. This is particularly relevant in this financial context, since the coefficient of variation measures how much volatility, is assumed in comparison to the amount of return expected from investments. However, since the mean returns are negative its financial interpretation would be misleading.

The last column of Table 3 provides a variance measure that quantifies the deviation of the distributions of a cluster with respect to its prototype. It is a dispersion measure for histogram data based on the L2 Wasserstein metric Irpino and Verde (2015). This statistic measures how much representative is the prototype of a cluster. According to this statistic, Cluster 3 would be the more uniform cluster, while Cluster 5 would be the more heterogeneous.

The first column of Figure 6 shows the prototypes of the five clusters in each row, while the rest of the columns show relevant cryptocurrencies from each cluster. It is interesting that except for the prototype of Cluster 1, the others exhibit a similar shape, where the main differences lie in the range of the distribution (note that each plot has a different range for the X axis) and in the tail behaviour. We will describe them below:

- **Cluster 1**: The prototype shown in Fig. 6(a) has a mean return of -0.13 and the highest kurtosis (13.43). The standard deviation of this prototype is slightly lower than that from Cluster 1 prototype, however, the shape of the distribution is different, because here the tails are thicker. The Wasserstein variance associated with the mean distribution (0.025) suggests that the cluster is homogeneous and has a cardinality of close to 500 cryptocurrencies that represent around at 30% of the sample. Some of the most representative cryptocurrencies in this cluster have a high market cap (P99), for example, `BITUSD` (high capitalization along 2018 but in a downward trend), `CHAT` in Fig.6(b), `KEY` in Fig.6(c) (high trading volume in the second half of 2018), `MAN` (increasing trading volume along 2018, maximum at the end of the year) and `OCN` (a token for peer-to-peer sharing economies such as Airbnb).
- **Cluster 2**: The prototype shown in Fig. 6(d) (green color distribution) has the lowest mean (-0.50) and median (-0.51) return among the clusters, and the highest coefficient of variation (-0.75). The cluster variance (0.079) points out a quite homogeneous cluster. This cluster has a cardinality of 147 cryptocurrencies and concentrate all no-traded cryptocurrencies (92), lowest market cap (P70) for most of the cryptocurrencies into this cluster. Representative into the cluster by market cap are 365 in Fig.6(e), `ACN`, `CBX` or `ALT` in Fig.6(f).
- **Cluster 3**: The prototype shown in Fig. 6(g) has a mean return close to zero (-0.01) and the most moderated volatility (0.11) and the shortest observed

range between minimum and maxium returns. According to the Wasserstein variance, this cluster is the most homogeneous, which is specially interesting given that it has the highest cardinality with more than 1000 cryptocurrencies (around 60% of the sample). Unsurprisingly, this cluster allocates the cryptocurrencies with the highest market capitalization, including `BTC` in Fig.6(h), `BCH`, `EOS`, `ETC`, `ETH` in Fig.6(i) and others (`HSR`, `ICX` or `LTC`). Given the size of the cluster, these cryptocurrencies represent the predominant behavior in the market, which unsurprisingly is the most moderate behaviour and includes the most popular cryptocurrencies.

- **Cluster 4**: The prototype shown in Fig. 6(j) is characterized by negative mean returns (-0.04), notable volatility (standard deviation of 0.87) and fat tails with very high kurtosis (11.95). The coefficient of variation is low too (-19.97). The cluster is not very homogeneous compared with the mean distribution (0.128). The cardinality of this cluster is low (around 60 cryptocurrencies) and some of the representative cryptocurrencies are NAS (most of the trading volume in 2nd and 3rd quarters of 2018), `NKC` (high trading volume since February 2018 and very important trading volume in Aug 18), `POLY` in Fig.6(k) (launched in January 2018), `FSN` (higher volume activity in 2nd and 3rd quarter of 2018 with a peak in August), `JNT` in Fig.6(l) (higher volume activity in 3rd quarter) or `MNTP` (no continuity on the trading volume with sporadic peaks).
- **Cluster 5**: The prototype shown in Fig. 6(m) has a mean returns closer to zero (-0.09) but the highest standard deviation (3.12), which causes the lowest coefficient of variation (-32.90). The shape of the cluster is almost symmetric (0.05) with a moderate kurtosis compared with the others clusters (5.66). We find the highest negative and positive returns in this cluster. This cluster is the most heterogeneous compared with the mean distribution (1.116). Unsurprisingly, it has the lowest cardinality with only 16 cryptocurrencies, which is around the 1% of the sample. Some of the representative cryptocurrencies are `B2X` in Fig.6(n) (low trading in 2018), `ITT` in Fig.6(o) (very active trading volume in January 2018 and along and a peak in July but no activity since that time, no trading volume in 2019), `LBTC` (launched in 2017, discontinuous activity along 2018 with no activity at all from September to end of November), `PFR`, `STAR` (noted in Cluster 2 of K-means), `YOVI`, `AMIX`, `ELTCOIN` (noted in Cluster 2 of K-means) or `FLLW` (some activity the first 2-3 months of 2018, low trading volume in the remaining part of the year).

The HistDAWass clustering shows that is possible to effectively discriminate the log-return distributions taking into account central tendency, dispersion and shape.

Clustering results of the log-return time-series representation

The TADPole clustering Begum et al. (2015) has better performance with a $k = 3$ value according to the Calinski-Harabasz index. Figure 7 represents the time series of the medoids of each cluster so they are observed objects (time series of cryptocurrencies). Figure 8 shows the annual and quarterly density functions of the three medoids.

- **Cluster 1**: The medoid of this cluster in Figure 8(b) shows a time-variation around zero with return peaks positive and negative up to (-0.2, +0.2). The central part of the distribution is heavily concentrated around zero, but with extreme volatility. The quarterly average returns changes smoothly starting with a low but positive value the first quarter, negative the second and third, and positive the fourth. This cluster has the lowest cardinality (22 cryptoassets). The medoid of this cluster is the time-series `LINK` (Chainlink's native token, known as `LINK`, is used to pay the network's node operators, or oracles, for providing secure data feeds). Other cryptocurrencies in this cluster are `LTCU`, `PPC`, `SWT`, `AIR`, `NGC`, `PLR` or `ZSC`
- **Cluster 2**: The medoid of this cluster in Figure 8(c) shows a consistent average returns above zero. The density functions have three modes and they are greater than or equal to zero. However, the last two quarters of 2018 exhibit fat negative tails with ranges over -0.1. The cardinality of this cluster represents around a 49% percentage of the cryptocurrencies and it includes some of the highest market cap cryptocurrencies `BTC`, `HSR` (noted in Cluster 3 of Hist DAWass), `ICX` (noted in Cluster 3 of Hist DAWass), `LTC` (noted in Cluster 3 of Hist DAWass) and `XRP`. The medoid is the cryptocurrency `XTO` (called Tao coin as well is a token for music streaming services).
- **Cluster 3**: The medoid of this cluster in Figure 8(d) has average returns below zero in all the quarters and the densities exhibit two modes smaller than or equal to zero and occasionally large positive returns. The cardinality of the cluster is around a 50% of the total. This cluster includes most of the remaining highest market cap cryptocurrencies as `EOS`, `ETC`, `ETH`. The medoid is the cryptocurrency `ZNE` (Zone coin with more trade activity in the first quarter of 2018 with the more important peak of trade volume in July, flat trading volume the remaining part of the year).

We can see that the TADPole clustering for the return time series effectively identifies three different clusters taking into account the time series trend and dispersion over time. In Table 4 we show the variability of the clusters, measuring the variability as the mean distance (DTW+LB) to the centroid and its standard deviation with LB as *Lower Bound*. The variability is quite similar in all the clusters, being cluster 1 the most homogeneous and cluster 3 the less. However, according to the standard deviation and the coefficient of variation the dispersion within the clusters is quite high.

Intersection of clusters

For the sake of comparison, Figure 2 shows the three clustering results on the same annual return-volatility plane. In each plot, all cryptocurrencies are site in the same location, but the colour scheme in each plot represents the respective clustering results. In the plot, we have marked the cryptocurrencies with highest market capitalization. We can see that most of them are very located in a precise area, below the point $(0, 0)$.

The polygons and the colours reveal that the results of the three techniques are overlapped because respond to a different dimensionality on the objects. The only exception is the Cluster 1 of K-means in Fig.2(a) and Cluster 5 of HistDAWass in Fig.2(b) which are mostly the same. These plots confirm that each clustering algorithm takes into account different aspects of the cryptocurrencies and that their combination may provide further insights on the cryptocurrency market. TADPole clustering in Fig.2(c) is the more different on the groups compared with previous techniques overlapping all the cluster areas for the same return-volatility plane.

We analyze now the main groups of cryptocurrencies that remains together through the three clustering algorithms, it is what we call intersection clusters. Only 24 out of 45 ($3x5x3$ intersections) possibles are populated. Table 5 shows the 6 most numerous, those with cardinality greater than 100, represents the 75% of total market.

Intersection 1 and 2 have almost 300 cryptocurrencies. Both of them are characterized by cryptocurrencies that belong to Cluster 2 and 3 in the K-means and HistDAWass algorithms, which unsurprisingly are the most populated clusters for each algorithm. Both of them are characterized by low volatility and (negative) close to zero average returns. However, in Intersection 1 we can find cluster 3 of the TADPole algorithm, while in Intersection 2, we can find cluster 2, which mainly differ in that in the first case it has negative quarterly average returns, while in the second case they are positive. In Intersection 1 we can find cryptocurrencies such as `EOS`, `GVT`, `MANA`, `ETH` or `ETC`. While in Intersection 2 we find some of the most popular highest market cap cryptocurrencies (`BTC`, `LTC`, `XRP`), and some others with lower market cap and higher returns (`AE`, `USDT`, `ZRX`).

Intersection 3 and 4 have around 200 cryptocurrencies with a high influence of K-means and Hist DAWass clusters. These intersections are characterized by cryptocurrencies that belong to Cluster 3 in the K-means and to Cluster 3 in the Hist-DAWass algorithm 6(g). The main difference with the previous intersections is that Cluster 3 of K-means corresponds on average with negative daily mean-returns but moderate volatility 3(a) so the average returns are lower as well for this intersection.

In the case of Intersection 3 we find one of the highest market cap cryptocurrency (`BCH`), and others with higher market capitalization (`GNT`, `LSK`, `QTUM`). While in the case of Intersection 4, the negative effect on average on the returns introduce by K-means Cluster 1 is compensated in some way by the TADPole Cluster2 with a centroide with all quarters over zero 8(c), no high returns cryptocurrencies on this intersection (`DASH`, `SC`, `STRAT`).

Finally, in Intersection 5 and 6, we have cluster 3 from the k-Means, cluster 1 from HistDAWass and clusters 3 and 2 from TADPole, respectively. Cluster 2 from HistDAWass was more volatile than cluster 3 and has heavier tails. In Intersection 5 we find cryptocurrencies with average-high risk and average returns (`CMT`, `ETT`, `HST`). Intersection 6 allocate some cryptocurrencies with high market cap but low returns (`BCD`, `SBTC`, `GEO`).

In the alluvial plot shown in Figure 9 we show how are related the different clusters of the different algorithms. It makes possible to appreciate both, the main trends already commented and those more subtle. For example, we can see that the smallest clusters in K-means and HistDAWass (Cluster 1 and Cluster 5, respectively) share most of the cryptocurrencies. In that sub-group of very volatile cryptocurrencies we find `AMIS`, `B2X`, `ELTCOIN`, `FLLW`, `GOOD`, `ICE`, `ITT`, `LBTC`, `PFR`, `REX`, `RIPT`, `STAR`, `WAND`, `XIN`, `YOVI` and `ZCG`. Then the group diverges and relates with the two main clusters of the TADPole algorithm, which means that the temporal evolution is more conventional with mean return in quarterly basis positive or negative.

Interestingly, the smallest TADPole cluster (Cluster 1) is not heavily related with any other cluster. This means that its peculiar time series evolution as we see in Fig. 8(a) is not particularly related with the prototypes of the aggregated representations, namely as return distributions and mean-standard deviation bi-variate or two-moments representations.

Finally, we mention that DEUR is the only cryptocurrency that is not pair-combined with any other cryptocurrencies along the three techniques.

Heavy-tail cryptocurrencies on the clusters

Finally, we mention where are allocated the cryptocurrencies with more extreme behaviour, 461 in total. The Table 13 shows the distribution on the different clusters for each one of the techniques respect to the total cryptocurrencies allocated in that cluster. We conclude that heavy-tail distributions are more often allocated in Cluster 1 in K-means and Cluster 2 in Hist DAWass. We have already commented that Cluster 1 in K-means allocate the highest volatile cryptocurrencies and that correspond with heavy-tails cryptocurrencies as well. As we commented, Cluster 2 in Hist DAWass allocates the more negative-return cryptocurrencies so we conclude that heavy-tails are more strong in negative part of the distributions (or histograms for Hist DAWass clustering).

Association tests

As we explained in Methods sections, we rely on exact Fisher tests base on Monte Carlo simulations for the significance tests on the association between the variables. P-values of Fisher test are depicted graphically in Fig. 10 with the results of the Fisher tests among the categorical variables in Table 1 and the clusters (including the combination of clustering results). P-values lower than 0.01 are represented in purple colour addressing the more significant associations.

The goal of the association tests is to enhance the characterization of the clusters based on the prototypes that we explained in previous Section. We group in a red box the area with the associations between the clusters and the market categorical variables.

We represent in Figure 11 the mossaic plots portraying Person's residual of some relevant pair-variables. As we explained in Methods section, the height of the box is proportional to the corresponding Person's residuals representing the difference between observed and expected frequencies, while the width is proportional to the square root of the estimated expected counts. The colour intensity is proportional to the absolute value of the residual.

Association between market cap, volume and clustering results

According to Table 6, the Cluster 3 of K-means, we recap that it is the one with the prototype with the most pronounced negative mean returns, is associated with the higher Volume percentiles (P80, P90 and P99) with standarized residuals 4.36, 4.35 and 5.71 respectively. However, Cluster 1 with the least pronounced negative mean returns, is associated with the lower percentiles (P70) with the highest residual 8.93. This is an interesting association since Volume was not considered as variable in the clustering process and shows an interesting and significant association for the behaviour of the cryptocurrencies that are not so popular with lower Volume or liquidity.

Finally, the association with the cluster for the highest market cap (*P100*) is not very strong but significant with a standardized residual of 3.71, most of the highest market cap cryptocurrencies are allocated in Cluster 2 . For instance, some of the cryptocurrencies with highest capitalization (`BTC`, `EOS`, `ETC`, `ETH`, `LTC` and `XRP`) are located in Cluster 2.

According to Table 6 for Hist DAWass which shows the association for the case of the HistDAWass clustering, Clusters 1 and 2, whose prototypes had the lowest mean returns, are strongly associated with lower `Volume` cryptocurrencies with residuals 12.25 and 3.72, while Cluster 3, whose prototype had the least pronounced negative average returns and the lowest volatility, is associated with the highest percentiles with 7.85 as standardized residual por `P99`. It is also possible to see weaker associations in the smaller clusters (Cluster 4 and 5).

For the assocation between Market cap and Hist DAWass we confirm a high significance on the assication between Cluster 1 and the lowest market cap percentiles with standardized residuals of 8.07. Cluster 3 groups medium-high market cap cryptocurrencies `P90` and `P99`

Since we can find association in all the clusters, we confirm that the screening by market cap variable is equally significant for both techniques K-means and HistDAWass although the granularity is not too much fine separating the cryptocurrencies in two major groups, one for the lower market caps in one or two clusters and the remaining in another cluster.

Association between financial ratios and clustering results

Table 8 shows the strong association (standardized residual of 17.79) between the K-means Cluster 1 and the Extreme Beta values, consistent with the highest volatility of that cluster. Extreme Beta values (`ICE`, `ITT`, `PFR` and `STAR`) are associated with Cluster 1 with the more volatile cryptocurrencies (`BLX`, `RIPT` or `XIN*`). On the opposite, Cluster 2 that allocates cryptocurrencies with positive and moderate negative mean returns is associated with a high significance (standardized residual 6.70) with low volatility (*LowVol*) Betas (`BTC`, `DCN`, `WAVES` or `WBTC*`) . . Finally, Cluster 3 is associated (standardized residual of 5.79) with cryptocurrencies with high volatility Betas (*HighVol*) (`ADA`, `BCH` or `SALT`) .

We confirm for Hist DAWass in Tab 8 the high screening capacity if this technique by separating with a high significance *NegBeta* in Cluster 1 and 2, *LowVol* with a reasonable residual of 3.1 in Cluster 3, *IndexLike* in Cluster 3 as well and *Extreme* in Clusters 4 and 5 with the highest residuals (10.33 and 19.24)

Time-series clustering algorithm (TADPole) exhibits significant association with Sharpe ratio in 7

We can see that *ERP* (Excess Return Positive) category is associated with Cluster 2 (BTM, SC, DNT, LEND or WINGS) with very high standardised residual (10.60) and the *SRF* (Small Risk-Free) class in Cluster 3 (EOS, ETC, ETH, NEO or ZEC) with a high residual (11.65) as well. The higher quality Sharpe ratio `Acc` values are significantly associated with cluster 2.

Summarizing, the association of the clustering results, *K-means* and *Hist DAWass* clusters are associated with the market cap, volume and the Beta. Moreover, the TADPole clustering is associated with *Sharpe ratio* .

Association test for intersection of clusters

As we saw in Fig. 10, the cluster intersection (Combi variable) is significantly associated with most of the variables. The intersections provide a better characterization of the cryptocurrencies because of smaller groups, where it is easier to find stronger associations inherit of the combined clusters. 6, 8 and 7 show the association between different categoric variables and the more relevant intersections.

For `Volume`, Clusters 3 and 4 with standardized residual from 4.53 to 7.35 allocates higher liquidity cryptocurrencies with `P90,P99` (`ADT, BLOCK, CND`) and even *P80* percentiles (`FLIX, LDC, RVT`). The highest percentile *P100* is mostly allocated in Intersection 1 (`EOS, ETC, ETH`)with 4.02 as standardized residual. Lower percentile *P70* is mostly allocated in Intersections 1 (coincidence *P100*),2 and 5,6.
Lower market cap cryptocurrencies are mostly allocated in Intersections 5 (`ANTI, BBT, XMG`),6 (`BTA, CNT, NTRN`) with the higher standardized residuals. Medium cap are mostly allocated into the intersections 3 (`ADT, BTX, ION`) and 4 (`BAY, LEND, SKY`).

For the Sharpe ratio, the more acceptable for investment cryptocurrencies (`Acc`)are mostly allocated into the Intersection 2 (`WAVES, XRP, ZEN`). Exceed Return Positive (*ERP*) are divided into Intersections 2 (`AC, ZRC, ZRX`) and 4 (`ADA, HSR, SC`).
There is not any *Extreme* `Beta` for the higher cardinality Intersections as we see on the Table 8. We can see a good screening on the Beta values with high standardized residuals for Intersections 5 (`FRX,PPP, XPY`), 6 (`GLC, TIT, XHI`) for *NegBeta*, Intersection 2 (`BTC, WAVES, WBTC*`) for *LowVol* and Intersections 3 (`BCH, QTUM, XVG`) and 4 (`ADA, HSR, STRAT`) for *HighVol*. Finally, as expected, the combined cluster variable (`Combi`) inherit the associations of the differente clustering techniques. and it is associated with all considered categorical variables except with the technological ones.

Associations for the technological variables
It is worth noting that while technological variables are not associated with any clustering results, they have significant relationship with the market cap (`PercMKCaP`) and volume (`PercVolume`) of trading (grey box). For example, in Table 12 there is a significant association between `Scrypt` (7.58 standarized residual), `SHA256` (3.58) and `X11` (6.65) encryption algorithms and the percentile (P70) of market cap as well. Encrypted algorithms `CryptoNight-V7, Ethash, Ouroboros` seems more associated to the highest market cap percentile (P100).

Concerning the consensus algorithm (`ProofType` variable) in Table 11, *PoS* (3.74), *PoW/PoS* (9.09) and *PoW* (4.54) are clearly associated to the lower percentiles (P70) of market cap.

Associations with the age (maturity) of the cryptocurrencies
Table 9 and Figure 11 shows the association between `Age`, *K-means* and *HistDAWass* clustering results. More particularly, the Cluster 2 of the K-means, which was characterized by low volatility and negative and close-to-zero average returns, is associated with younger cryptocurrencies (*D4*). In the same way with the Cluster 1 of *Hist DAWass* (*D4*), most of the younger cryptocurrencies of the Cluster 1 of *HistDAWass* remain together into the Cluster 2 of K-means. We remind in Table 2 that the cardinality of Cluster 2 of DAWass is 147 so 80% of the total cyrptocurrencies in this Cluster are recent cryptocurrencies with the lower mean value for the returns 3 (-0.50) and medium volatility (0.38).

More mature cryptocurrencies (*D10*) are associated with *Hist DAWass* Cluster 3 that are also the higher market cap clusters (`BTC, DASH, ETH`). Average maturity (*D5* (`ALIS,HDG, WTT`) and *D6* (`ATM*, BTH, GRE`)) cryptocurrencies are associated into *Hist DAWass* Cluster 1. In Figure , we see very high Person's residuals (up to 13) and a well-defined granularity by age for the Hist DAWass clusters confirming this technique helfull for maturity screening.

Considering both clustering techniques, K-means and Hist DAWass and the maturity, we confirm that lower maturity cryptocurrencies seem allocated in lower volatility and coefficient of variations clusters. We confirm an association between highest market cap, higher maturity, lower volatility 3 and higher liquidity in Cluster 3 of *Hist DAWass* (`BCH, BTC, DASH, EOS, ETC, ETH, IOT,LINK, LTC, NEO, WAVES, XLM, XMR, XRP, ZEC, ZRX`).

For the intersection of clusters, Table 9 shows how the higher maturity (*D10*) cryptocurrencies are allocated into the Intersections 3 and 4 with very high standardized residual (7.20, 8.37 respectively). Average maturity (*D5*, *D6*) in Intersection 5 and 6, and younger cryptocurrencies (*D4*) are significantly allocated into the Intersection 6 (`EBC, ICOB, PULSE`).

Discussion
In this section, we summarise the main results obtained in the clustering and the association tests.

- We confirm the existence of a structure on the market that allow us to segment the cryptocurrencies in different clusters. The optimum number of clusters remains low, independently of the representation considered, which seems to point out a high degree of homogeneity despite the high number of cryptocurrencies.
- The bi-dimensional or two-moments representation by the classic K-means works quite well to segment separately by the returns and volatility in three major groups. However, the log-return distribution and the HistDAWass clustering offered a more subtle discrimination of the cryptocurrencies specially taking into account the combination of both moments, as we could see in the coefficient of variation values. Thus, it seems a more suitable profiling tool for investors.
- Both K-means and HistDAWass partitions split the data set into two groups according to market capitalization and Volume.
- The log-return time series representation provided a low number of clusters. However, they were significantly associated with Sharpe ratio by highest and lowest values.
- The K-means and the HistDAWass clustering provide an interesting association with the age or maturity of the cryptocurrencies. The results seem to point out that younger and older cryptocurrencies have particular and different return distribution.
- The intersection of clusters inherit by combining the association rules that we had observed separately for each one of the clustering algorithm. This is confirmed for Age, MkCap variables and the different financial ratios.

Conclusion

In this work we analysed the whole cryptocurrency market in 2018, that is all the cryptocurrencies traded in 2018, with a novel method that involved the combination of three different clustering algorithms. Each method used a meaningful representation considering different aggregation or granularity level of the daily returns: from the yearly average return and volatility, the yearly distribution of returns, and finally the observed time series of daily returns. For each representation we used prototype based clustering methods, so the prototypes of each cluster are meaningful and make possible to interpret the result.

Furthermore, we enhanced our profiling of the cryptocurrency market with association tests that validate the potential relationship between the clustering results and other descriptive features of the cryptocurrencies (technological attributes, financial ratios and age). These tests make possible to determine whether some features are related with a particular financial performance detected by the clustering algorithms.

Our analysis confirmed that there is an underlying structure of the data. Each one of the clustering algorithms revealed different aspects of the cryptocurrency market. Furthermore, the combination of the different the clustering results proved valid to detect the main trends in the cryptocurrency market, but also particular behaviours beyond these trends.

Finally, the association tests served to better describe the resulting clusters by adding the significant relationships found with the financial ratios, technological attributes and age of the cryptocurrencies.

In summary, we believe that the methodology used provides a descriptive tool supported by modern clustering techniques that may be useful for investors that need to understand the cryptocurrency market, as it reduces the dimensionality of the data set and identify the main trends in a descriptive manner. A straightforward extension of this research would include considering a longer time-frame for the data set just to investigate the dynamic evolution of the market structure and clusters beyond 2018. For further investigations, the associations of some of the key financial ratios and cluster associations could play an important role enhancing the performance of the algorithms for the asset selection and diversification of portfolios(Liu (2019), Platanakis et al. (2018), Brauneis and Mestel (2019)) or improving the forecasting performance (Mallikarjuna and Rao (2019)) to tackle the difficulty of a non-homogenous market.

Competing interests

The authors declare that they have no competing interests.

Author's contributions

The initial idea was conceived by JA. The experiments were designed by LL. The searching on the data bases, statistical analysis and software design as performed by LL. The work was drafted by LL and revised critically by JA. All authors read and approved the final manuscript.

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Figures

Tables

Additional Files

Additional file 1 — Sample additional file title
Additional file 2 — Sample additional file title
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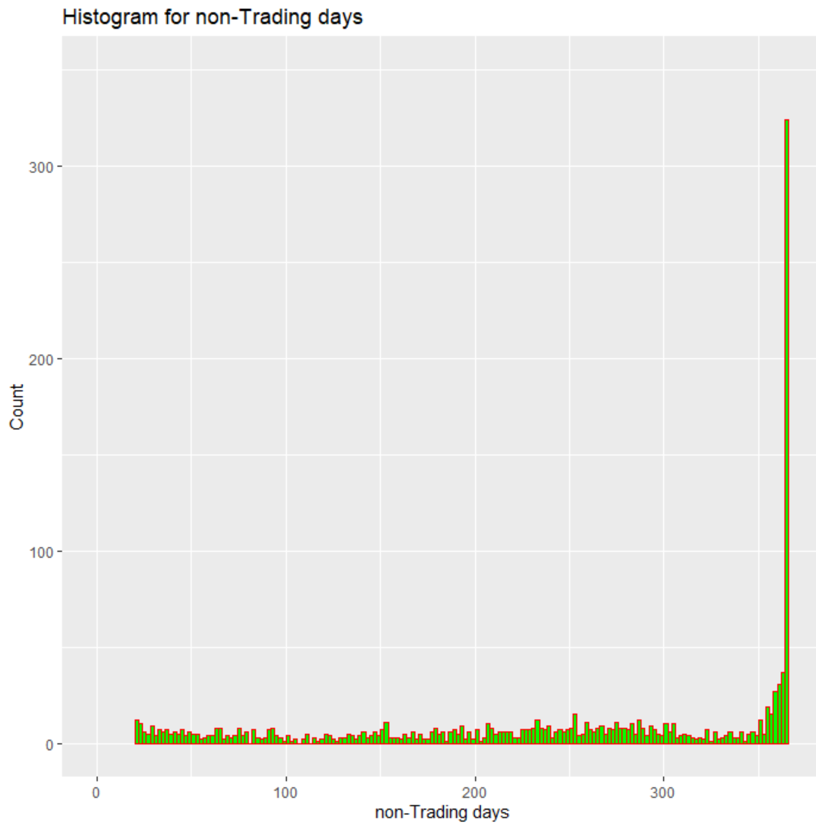
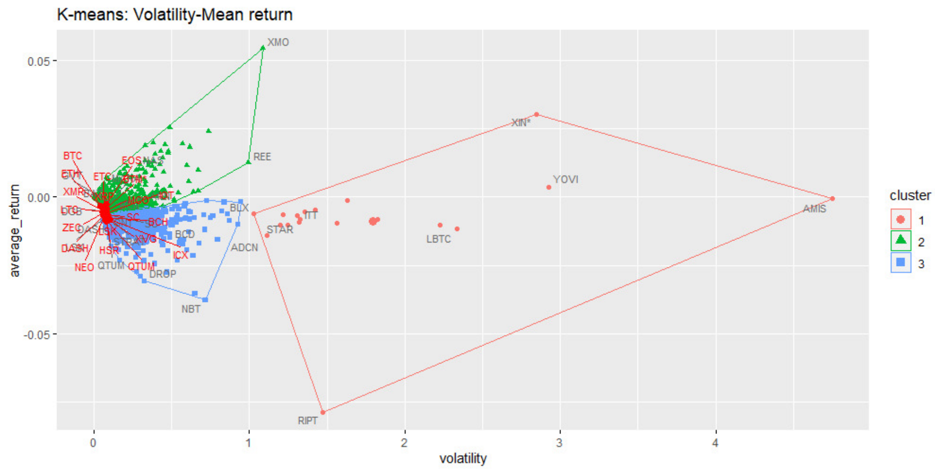


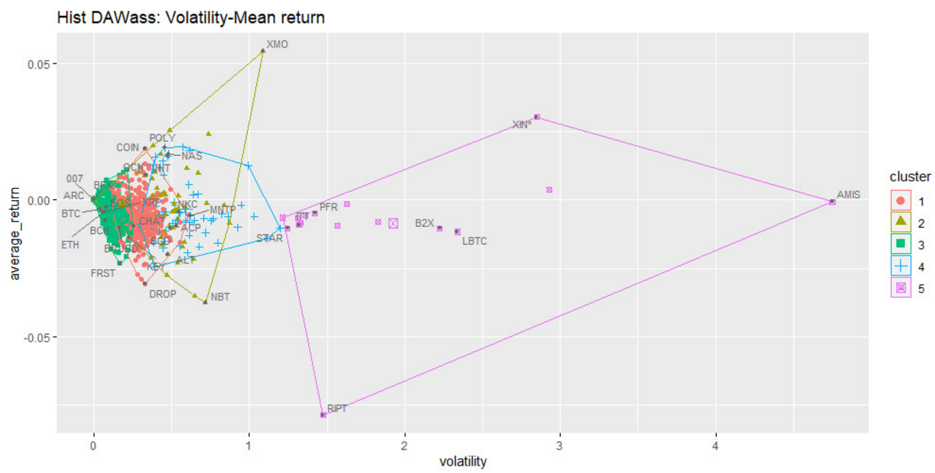
Figure 1 Histogram of cryptocurrencies according to the days with no activity

Variable	# Levels	Values
Algorithm	73	Encryption algorithm (SHA256, Ethash, X13, X11,...)
ProofType	39	Consensus algorithm (PoW, PoW/PoS,DPoS..)
Volume	5	Percentiles of the volume negotiated. Namely, *P70* for volume values lower than the P_{70} percentile, *P80* for values higher than the P_{70} and lower than the P_{90}, and similarly *P90*, *P99* and *P100*.
MkCap	5	Percentiles of the market capitalization. Namely, *P70* for market cap values lower than the P_{70} percentile, *P80* for values higher than the P_{70} and lower than the P_{90}, and similarly *P90*, *P99* and *P100*.
Beta	6	Beta values divided into the following categories: *NegBeta* for beta values lower than -0.01 *CashLike* if beta is to equal or higher than -0.01 and lower than 0.01 *LowVol* if beta is equal to or higher than 0.01 and lower than 0.95 *Indexlike* if beta is equal to or higher than 0.95 and lower than 1.05 *HighVol* if beta is equal to or higher than 1.05 and lower than 100 *Extreme* if beta is higher than 100
Sharpe	6	Sharpe ratio divided into the following categories: *SRF* (Small Risk-free) for negative values *ERP* (Excess return positive) for positive values lower than 0.5 *ACC* (Acceptable) for values equal to or higher than 0.5 and lower than 1.0 *GOOD* for values equal to or higher than 1.0
Age	7	Deciles of the age variable (time on the market). We use the same partition than in the M2 ratio.

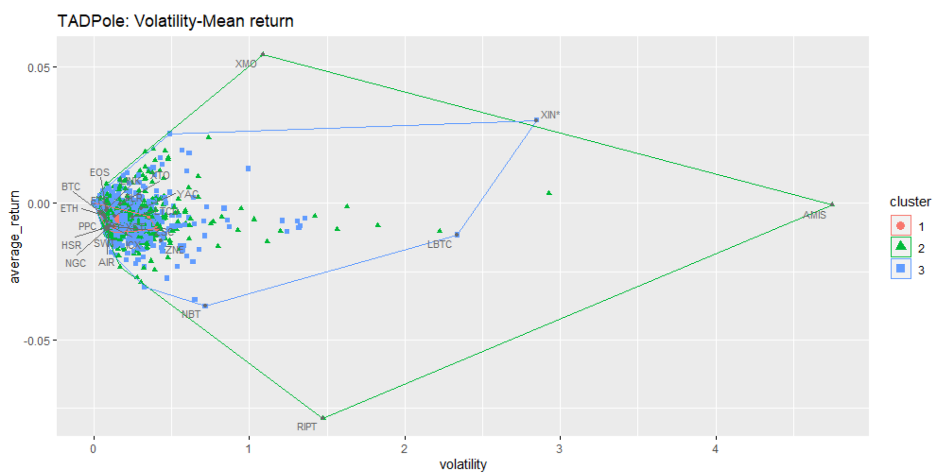
Table 1 Categorical variables used on the association tests and its values (*NA* was used for not available values)



(a) K-means clustering for ordinary variables with the position of highest market cap in red colours

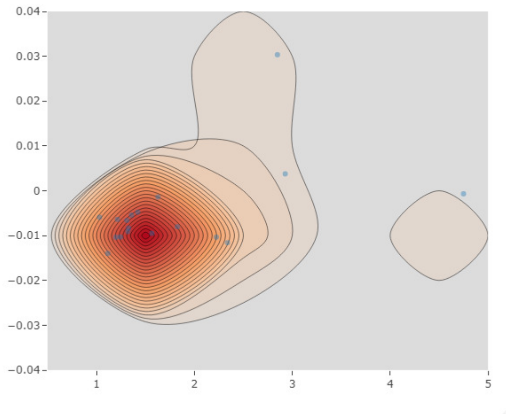


(b) Histogram DAWass clustering for ordinary variables

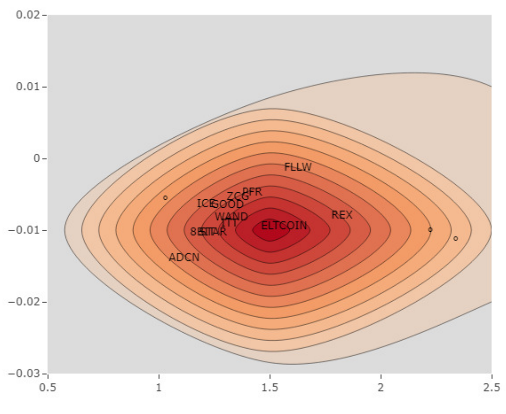


(c) TADPole clustering for ordinary variables

Figure 2 Volatility-Average return (two-moments) plane in ordinary values with the vertex names and the more representative cryptocurrencies in terms of market cap for the different clustering techniques



(a) Cluster 1



(b) Detail of Cluster 1

Figure 3 Cluster 1 represented in the bi-dimensional space $(\bar{r}, \sigma)$ by a 2D density contour plot.

	K-means			**HistDAWass**			**TADPole**		
	Card.	*Mean*	*Std.Dev.*	*Card.*	*Mean*	*Std.Dev.*	*Card.*	*Mean*	*Std.Dev.*
Clus. 1	19	-0.008	1.795	496	-0.134	0.337	22	-0.001	0.080
Clus. 2	903	-0.002	0.130	147	-0.503	0.378	843	0.026	0.046
Clus. 3	801	-0.009	0.229	1007	-0.011	0.108	858	-0.028	0.047
Clus. 4				57	-0.044	0.867			
Clus. 5				16	-0.095	3.123			

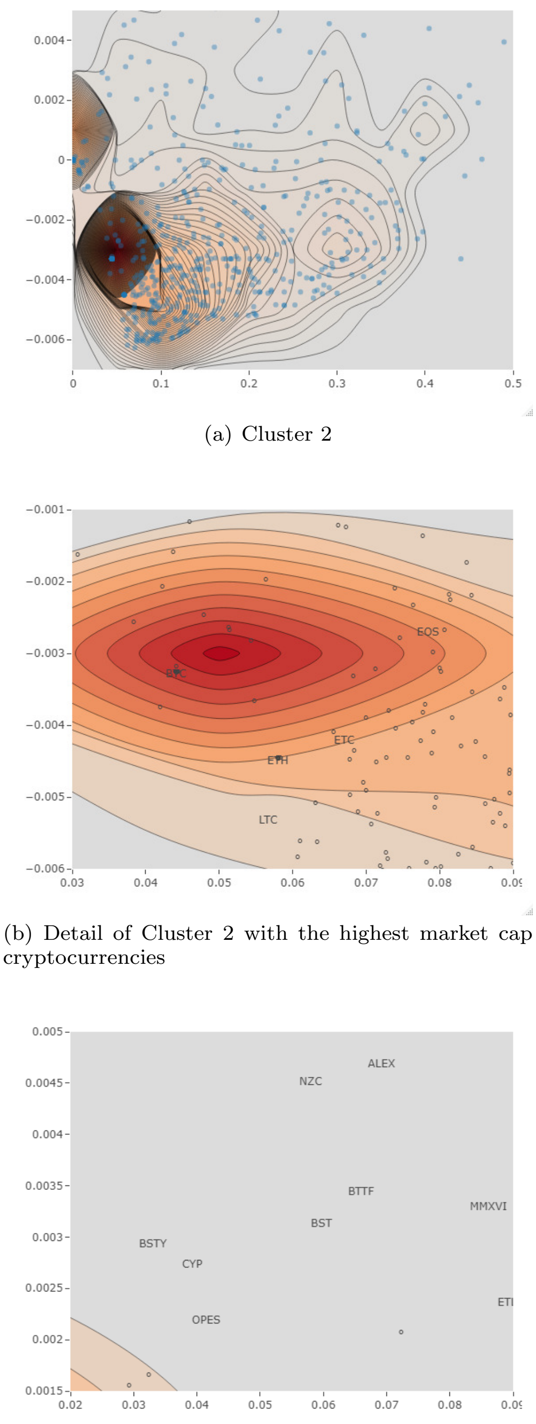
Table 2 Cluster cardinality, mean value and standard deviation of the centroid or prototypes for the clustering methods. For Hist DAWass and TADPole we compute the mean and standard deviation of the prototypes.

	Mean	Std. Dev.	Coef.Var.	Skew.	Kurt.	Med.	Min.	Max.	Var.Wass.
Clus. 1	-0.13	0.34	-2.51	0.82	13.43	-0.16	-2.24	2.36	0.025
Clus. 2	-0.50	0.38	-0.75	0.56	9.33	-0.51	-2.69	2.18	0.079
Clus. 3	-0.01	0.11	-10.06	0.28	7.10	-0.01	-0.55	0.62	0.005
Clus. 4	-0.04	0.87	-19.97	0.54	11.95	-0.08	-5.44	6.67	0.128
Clus. 5	-0.09	3.12	-32.90	0.05	5.66	-0.17	-17.56	17.56	1.116

Table 3 Descriptive statistics for the prototypes of the Hist DAWass clustering.

Cluster	Mean Dist.	Std. Dev.	Coef. Var.
1	4.31	3.04	0.71
2	4.60	3.29	0.72
3	4.85	3.53	0.73

Table 4 Variability of TADPole clusters with the mean distance (Mean Dist.) to the centroid, standard deviation (Std. Dev.) and coefficient of variation (Coef. Var.).

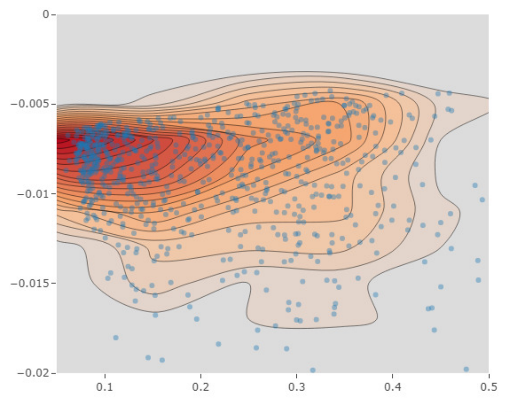


(a) Cluster 2

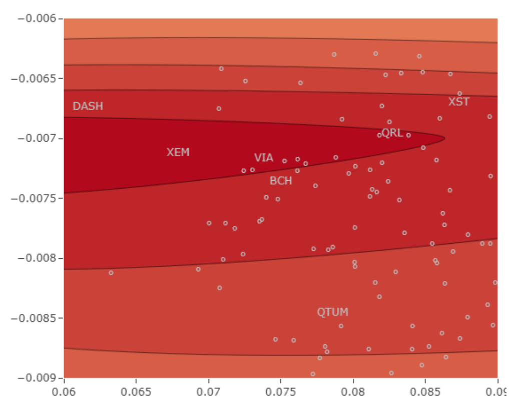
(b) Detail of Cluster 2 with the highest market cap cryptocurrencies

(c) Detail of cluster 2 for the high returns and low volatility cryptocurrencies

Figure 4 Cluster 2 represented in the bi-dimensional space $(\bar{r}, \sigma)$ by a 2D density contour plot.

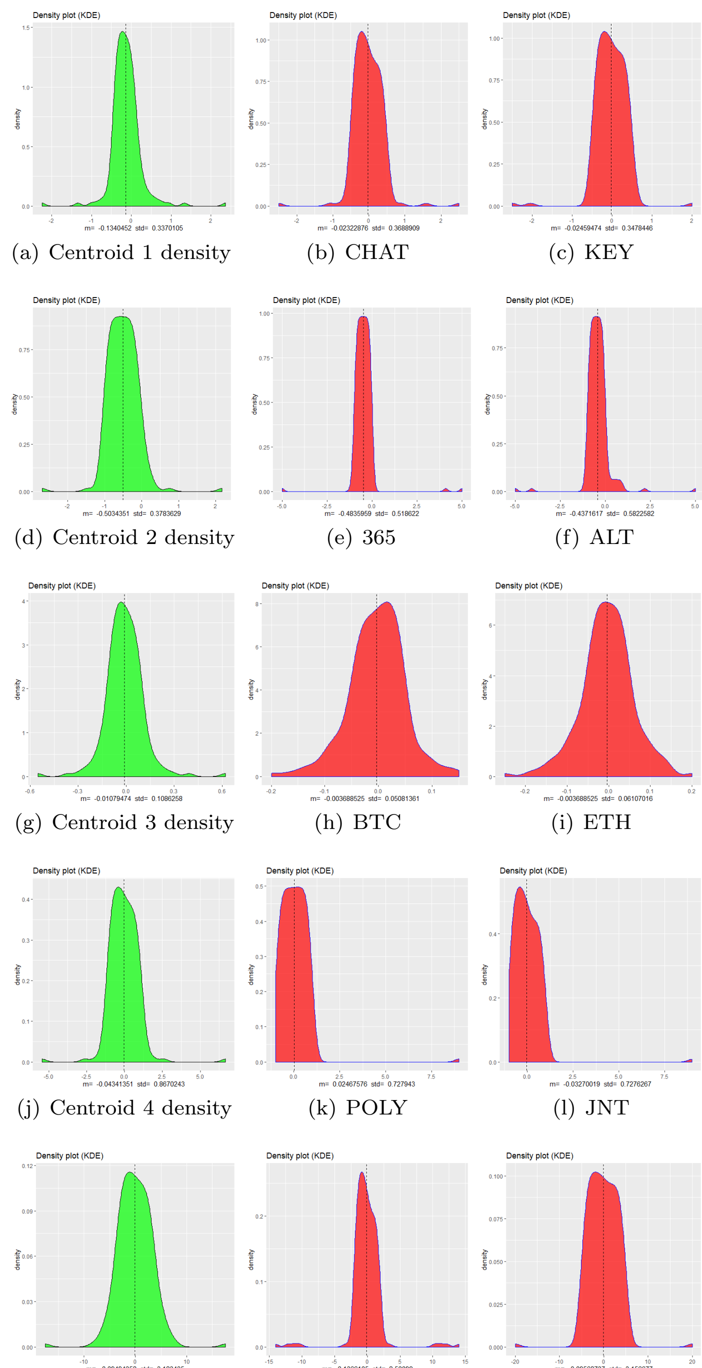


(a) Cluster 3



(b) Detail of Cluster 3 with the highest market cap cryptocurrencies)

Figure 5 Cluster 3 represented in the bi-dimensional space $(\bar{r}, \sigma)$ by a 2D density contour plot.



(a) Centroid 1 density (b) CHAT (c) KEY

(d) Centroid 2 density (e) 365 (f) ALT

(g) Centroid 3 density (h) BTC (i) ETH

(j) Centroid 4 density (k) POLY (l) JNT

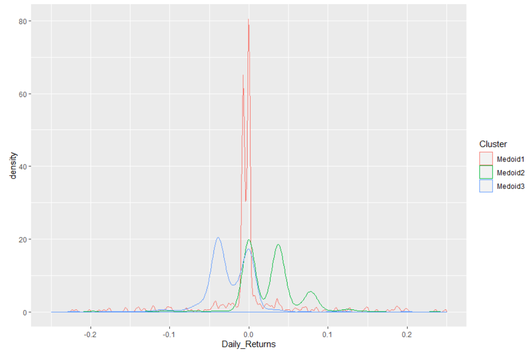
(m) Centroid 5 density (n) B2X (o) ITT

Figure 6 Density plot for prototypes (first column), and some representative cryptocurrencies of each cluster in terms of market capitalization (2nd and 3rd columns)

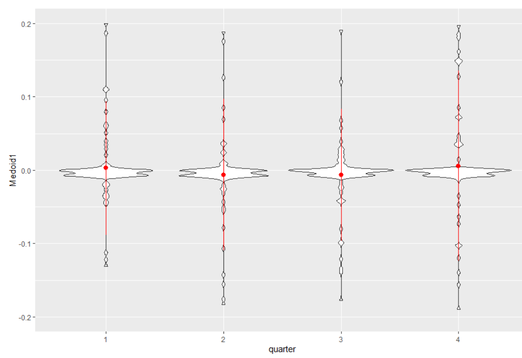
Figure 7 Medoids of the clustering results of the TADPole algorithm (time series of daily returns)

Intersection	Kmeans	HistDAWass	TADPole	Combi	N
1	2	3	3	1	295
2	2	3	2	2	294
3	3	3	3	3	208
4	3	3	2	4	196
5	3	1	3	5	166
6	3	1	2	6	148
7	2	1	2	7	97
8	2	1	3	8	78
9	2	2	3	9	57
10	2	2	2	10	54
11	3	2	3	11	20
12	3	4	2	12	18
13	3	4	3	13	18
14	3	2	2	14	15
15	2	4	2	15	10
16	2	4	3	16	8
17	1	5	2	17	8
18	1	5	3	18	8
19	2	3	1	19	7
20	3	3	1	20	7
21	3	1	1	21	5
22	1	4	2	22	3
23	2	1	1	23	2
24	2	2	1	24	1

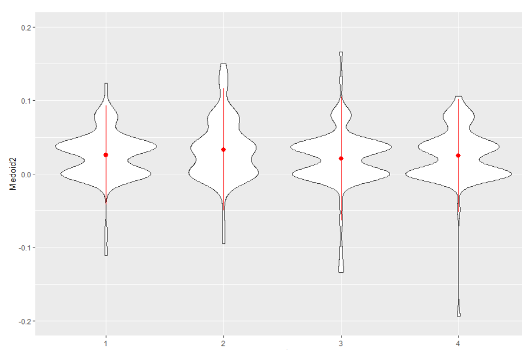
Table 5 Intersection of clusters across the different clustering algorithms, each column represent the cluster number. Intersections are sorted in inverse cardinality (N) order.



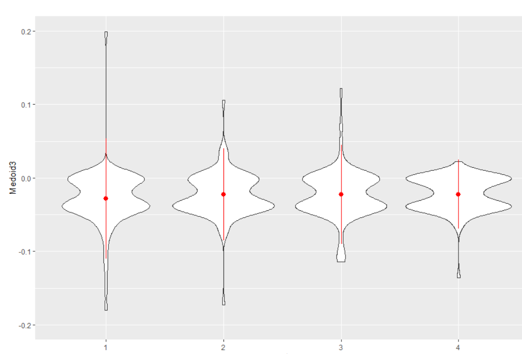
(a) Density plot of the three medoids



(b) Quarterly distribution of the Cluster 1 medoid (LINK)



(c) Quarterly distribution of the Cluster 2 medoid (XTO)



(d) Quarterly distribution of the Cluster 1 medoid (ZNE)

Figure 8 Density plot in Fig.a) and quaterly distribution of the TADPole medoids represented by violin graphs in Fig. b), c) and d) with the mean and standard deviation.

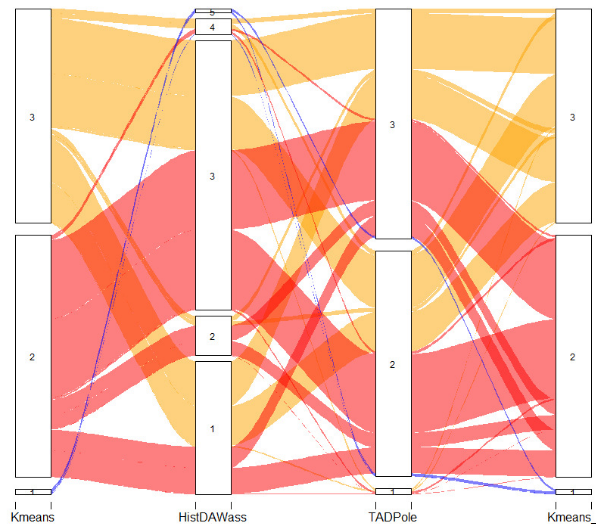


Figure 9 Alluvial plot showing the 'flows' of cryptocurrencies through the three clustering algorithms

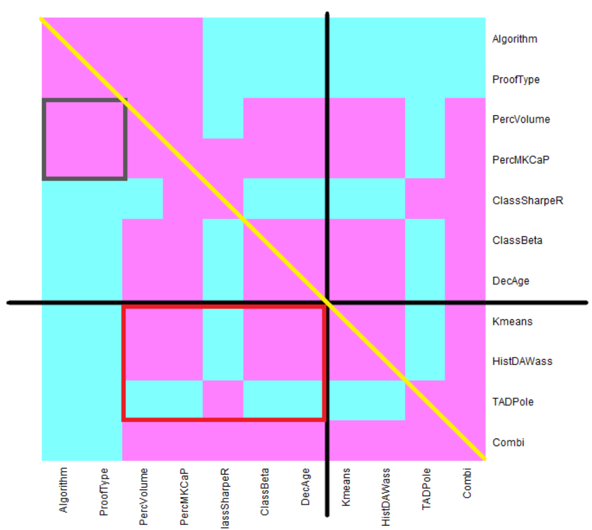
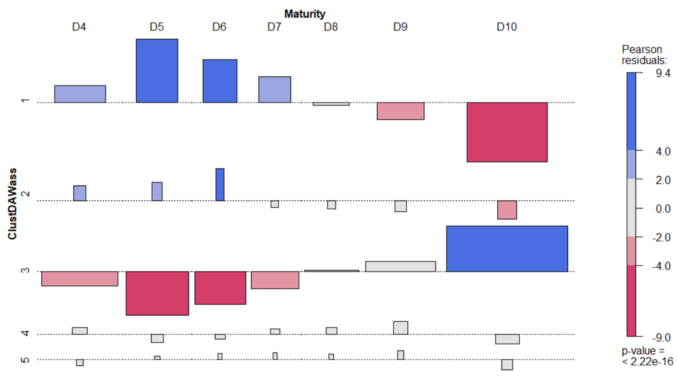
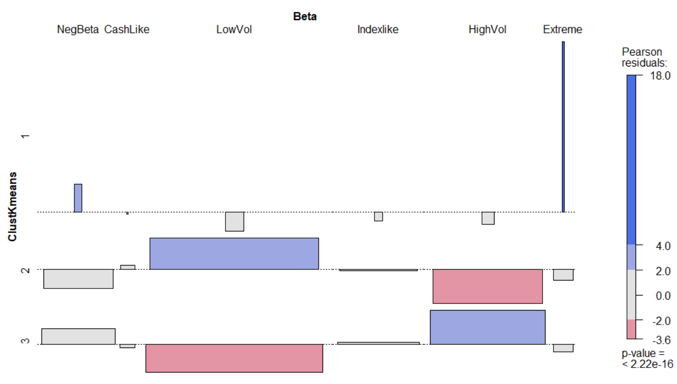


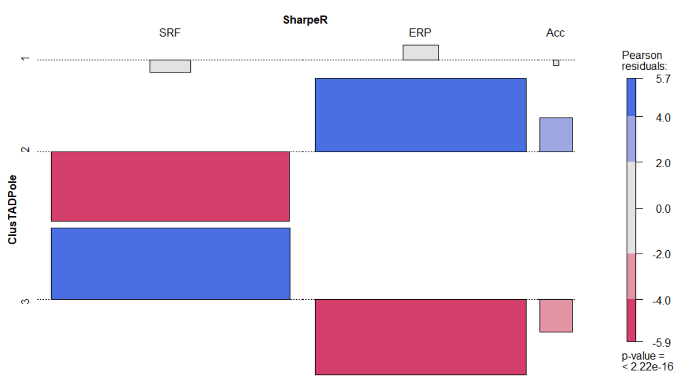
Figure 10 Matrix-type representation of the association tests using the Fisher's exact test. Binary coloured where pink colour means significant association at p-values lower than 0.01. Red box for cluster-categorical variables and grey box focused on the particular associations with the technological variables. Yellow line marks the trivial maximum association for the same variables



(a) Maturity VS Hist DAWass clustering



(b) Beta VS K-means



(c) Sharpe ratio VS TADPole

Figure 11 Pearson's residual representation for combination of different clustering techniques and categoric variables

Technique	Cluster/Intersection	P70	P80	P90	P99	P100
PercVolume VS K-means	1	-0.13	2.43	-1.05	-0.97	-0.43
	2	**8.93**	-4.73	-4.20	-5.57	2.61
	3	-8.90	**4.36**	**4.35**	**5.71**	-2.54
PercVolume VS Hist DAWass	1	**12.25**	-4.33	-4.82	-7.26	-3.67
	2	**3.72**	-1.71	-1.78	-1.66	-0.74
	3	-12.01	3.09	**5.09**	**7.85**	**3.71**
	4	-2.02	**3.36**	0.44	-0.95	0.22
	5	-0.48	2.78	-0.97	-0.90	-0.40
PercMKCaP VS K-means	1	1.15	0.28	-0.96	-0.91	-0.37
	2	**3.91**	-5.90	-1.77	0.20	**3.57**
	3	-4.08	**5.85**	1.92	-0.06	-3.51
PercMKCaP VS Hist DAWass	1	**8.07**	-1.70	-4.98	-4.64	-2.21
	2	2.36	-0.87	-1.63	-0.81	-0.63
	3	-8.37	1.88	**4.89**	**4.84**	2.59
	4	-0.44	-0.24	1.37	-0.16	-0.78
	5	0.94	0.44	-0.89	-0.84	-0.34
PercVolume VS Combi	1	**3.66**	-2.20	-2.62	-2.52	**4.02**
	2	**5.98**	-2.52	-2.51	-3.49	-0.41
	3	-10.25	2.57	**6.21**	**6.21**	-0.26
	4	-12.42	**6.39**	**4.53**	**7.35**	-0.21
	5	**7.16**	-3.21	-2.24	-3.95	-2.14
	6	**7.30**	-1.25	-3.96	-4.39	-1.97
PercMKCap VS Combi	1	2.27	-3.02	-2.45	0.86	2.97
	2	2.17	-3.34	0.40	-0.90	1.31
	3	-6.69	**3.98**	**4.80**	1.89	-1.54
	4	-6.33	**3.63**	2.72	3.31	-0.33
	5	**4.88**	-0.99	-3.38	-2.22	-1.72
	6	**4.87**	0.21	-2.94	-3.96	-1.58

Table 6 *Volume* and *Market cap* - Standardized Person's residuals

Technique	Cluster/Intersection	SRF	ERP	Acc
TADPole	1	-1.43	1.52	-0.44
	2	-11.32	**10.60**	**3.69**
	3	**11.65**	-10.95	-3.58
Combi	1	**5.83**	-5.49	-1.74
	2	-6.02	**5.20**	**4.13**
	3	**3.92**	-3.63	-1.53
	4	-4.67	**4.67**	0.11
	5	**3.93**	-3.68	-1.24
	6	-3.00	3.04	-0.15

Table 7 *Sharpe ratio* - Standardized Person's residuals

Technique	Cluster/Intersection	NegBeta	CashLike	LowVol	Indexlike	HighVol	Extreme
K-means	1	3.05	-0.17	-2.92	-0.97	-1.45	**17.79**
	2	-2.87	0.57	**6.70**	-0.18	-5.58	-1.51
	3	2.41	-0.54	-6.26	0.32	**5.79**	-1.13
Hist DAWass	1	**12.09**	1.57	-0.32	-5.84	-3.37	-1.90
	2	**3.97**	-0.28	-2.24	-0.94	0.74	-0.38
	3	-15.24	-1.29	3.10	**6.66**	2.83	-4.29
	4	**6.93**	-0.36	-5.47	-2.05	1.23	**10.33**
	5	2.02	-0.15	-2.70	-0.89	-1.34	**19.24**
Combi	1	-3.71	-0.90	4.50	-0.19	-2.92	-
	2	-4.07	0.49	**5.62**	0.57	-4.82	-
	3	-3.47	-0.79	-5.74	3.28	**6.20**	-
	4	-3.42	0.76	-5.41	1.99	**6.62**	-
	5	**7.87**	-0.65	1.73	-3.61	-3.53	-
	6	**10.52**	1.29	-1.69	-3.16	-1.61	-

Table 8 *Beta* - Standardized Person's residuals

Technique	Cluster/Intersection	D4	D5	D6	D7	D8	D9	D10
K-means	1	-1.14	0.32	0.76	2.48	0.63	1.18	-2.14
	2	**4.74**	-0.34	-1.75	0.91	1.33	-1.14	-2.79
	3	-4.56	0.29	1.63	-1.29	-1.43	0.96	3.11
Hist DAWass	1	3.27	**11.88**	**7.91**	**4.70**	-0.51	-3.35	-13.70
	2	2.41	2.85	**4.97**	-1.15	-1.32	-1.78	-3.64
	3	-3.99	-11.80	-8.80	-4.65	0.38	2.80	**15.08**
	4	1.08	-1.35	-0.83	0.83	1.06	2.05	-1.95
	5	-1.06	0.49	0.94	1.08	0.80	1.43	-1.98
Combi	1	1.70	-2.76	-1.40	0.19	0.24	0.36	0.51
	2	**4.71**	-1.10	-1.73	-0.15	1.93	-1.22	-2.13
	3	-5.47	-4.02	-3.05	-1.46	-1.82	3.07	**7.20**
	4	-5.61	-4.24	-2.99	-2.84	-0.54	1.55	**8.37**
	5	1.35	6.34	**7.38**	2.87	1.16	-2.07	-8.53
	6	**3.87**	**8.38**	**3.62**	2.16	-1.15	-2.38	-7.92

Table 9 *Maturity* - Standardized Person's residuals

	P70	P80	P90	P99	P100
DPoR	-1.20	-0.38	2.51	-0.37	-0.16
DPoS	-2.42	-0.45	-0.54	3.18	3.15
DPoS/LPoS	1.18	-0.54	-0.56	-0.52	-0.23
dPoW/PoW	-1.20	-0.38	-0.40	2.71	-0.16
LFT	-1.20	-0.38	-0.40	-0.37	6.23
LPoS	-1.20	-0.38	2.51	-0.37	-0.16
N/A	-9.62	2.12	5.00	6.76	0.69
PoA	0.83	-0.38	-0.40	-0.37	-0.16
PoB/PoS	0.83	-0.38	-0.40	-0.37	-0.16
POBh	-1.20	2.63	-0.40	-0.37	-0.16
PoC	-0.91	-0.66	0.99	1.14	-0.28
PoI	-1.20	-0.38	2.51	-0.37	-0.16
PoP	0.83	-0.38	-0.40	-0.37	-0.16
PoP/PoV/PoQ	0.83	-0.38	-0.40	-0.37	-0.16
PoPP	-1.20	-0.38	-0.40	2.71	-0.16
PoS	**3.66**	-1.65	-1.41	-1.74	-1.29
PoS/LPoS	-1.20	-0.38	-0.40	2.71	-0.16
PoS/PoB	0.83	-0.38	-0.40	-0.37	-0.16
PoS/PoW	0.83	-0.38	-0.40	-0.37	-0.16
PoS/PoW/PoT	-1.20	2.63	-0.40	-0.37	-0.16
PoSign	0.83	-0.38	-0.40	-0.37	-0.16
PoST	-1.20	-0.38	-0.40	2.71	-0.16
PoW	1.43	0.69	-0.73	-2.68	1.23
PoW and PoS	0.83	-0.38	-0.40	-0.37	-0.16
PoW/HiPoS	0.83	-0.38	-0.40	-0.37	-0.16
PoW/nPoS	-1.20	-0.38	-0.40	2.71	-0.16
PoW/PoM/PoSII	0.83	-0.38	-0.40	-0.37	-0.16
PoW/PoS	**7.34**	-1.51	-3.80	-4.65	-1.84
PoW/PoS	-0.26	1.59	-0.56	-0.52	-0.23
Pow/PoSC	-1.20	-0.38	-0.40	2.71	-0.16
PoWT	-1.20	-0.38	2.51	-0.37	-0.16
Proof of Authority	-1.20	-0.38	2.51	-0.37	-0.16

Table 10 *Consensus algorithm - Volume* Standardized Person's residuals

	P70	P80	P90	P99	P100
DPoR	-1.36	2.83	-0.36	-0.34	-0.13
DPoS	-1.69	-0.31	-0.36	1.64	3.91
DPoS/LPoS	1.04	-0.50	-0.51	-0.49	-0.19
dPoW/PoW	-1.36	-0.35	-0.36	2.91	-0.13
LFT	-1.36	-0.35	-0.36	2.91	-0.13
LPoS	-1.36	-0.35	-0.36	-0.34	7.42
N/A	-14.15	6.34	6.90	7.93	0.80
PoA	0.74	-0.35	-0.36	-0.34	-0.13
PoB/PoS	0.74	-0.35	-0.36	-0.34	-0.13
POBh	-1.36	2.83	-0.36	-0.34	-0.13
PoC	-2.36	-0.61	2.97	1.29	-0.23
PoI	-1.36	-0.35	-0.36	-0.34	7.42
PoP	0.74	-0.35	-0.36	-0.34	-0.13
PoP/PoV/PoQ	0.74	-0.35	-0.36	-0.34	-0.13
PoPP	-1.36	-0.35	-0.36	2.91	-0.13
PoS	**3.74**	-1.77	-0.76	-2.82	-0.88
PoS/LPoS	-1.36	-0.35	-0.36	2.91	-0.13
PoS/PoB	0.74	-0.35	-0.36	-0.34	-0.13
PoS/PoW	0.74	-0.35	-0.36	-0.34	-0.13
PoS/PoW/PoT	0.74	-0.35	-0.36	-0.34	-0.13
PoSign	0.74	-0.35	-0.36	-0.34	-0.13
PoST	0.74	-0.35	-0.36	-0.34	-0.13
PoW	**4.54**	-2.39	-1.69	-3.12	0.63
PoW and PoS	-1.36	2.83	-0.36	-0.34	-0.13
PoW/HiPoS	0.74	-0.35	-0.36	-0.34	-0.13
PoW/nPoS	-1.36	-0.35	-0.36	2.91	-0.13
PoW/PoM/PoSII	0.74	-0.35	-0.36	-0.34	-0.13
PoW/PoS	**9.09**	-3.38	-4.69	-4.72	-2.43
PoW/PoS	-0.44	-0.50	-0.51	1.82	-0.19
Pow/PoSC	-1.36	2.83	-0.36	-0.34	-0.13
PoWT	-1.36	2.83	-0.36	-0.34	-0.13
Proof of Authority	-1.36	-0.35	-0.36	2.91	-0.13

Table 11 *Consensus algorithm - Market cap* Standardized Person's residuals

	P70	P80	P90	P99	P100
536	-0.44	1.75	-0.51	-0.49	-0.19
Argon2	0.74	-0.35	-0.36	-0.34	-0.13
Argon2d	-1.36	-0.35	2.75	-0.34	-0.13
Blake	1.28	-0.61	-0.63	-0.60	-0.23
BLAKE256	-0.44	-0.50	-0.51	1.82	-0.19
Blake2b	-1.36	-0.35	-0.36	2.91	-0.13
Blake2S	1.28	-0.61	-0.63	-0.60	-0.23
C11	1.04	-0.50	-0.51	-0.49	-0.19
Counterparty	-1.92	4.00	-0.51	-0.49	-0.19
CryptoNight	0.91	-0.39	-0.45	-0.34	-0.49
CryptoNight-Lite	0.74	-0.35	-0.36	-0.34	-0.13
CryptoNight-V7	-1.92	-0.50	1.69	-0.49	**5.16**
Curve25519	0.74	-0.35	-0.36	-0.34	-0.13
Dagger	1.28	-0.61	-0.63	-0.60	-0.23
Dagger-Hashimoto	-1.15	1.23	1.17	-0.60	-0.23
DPoS	-0.72	-0.21	-0.27	0.83	1.84
Equihash	-2.62	0.75	-0.27	2.80	1.84
Ethash	-0.99	-0.11	-1.15	0.98	**4.37**
Groestl	-1.67	-0.71	2.39	0.94	-0.27
HybridScryptHash256	0.74	-0.35	-0.36	-0.34	-0.13
Keccak	-0.44	-0.50	-0.51	1.82	-0.19
Leased POS	-1.36	-0.35	-0.36	-0.34	7.42
Lyra2RE	0.42	0.89	-0.73	-0.69	-0.27
Lyra2REv2	-0.44	-0.50	-0.51	1.82	-0.19
Lyra2Z	-1.15	-0.61	1.17	1.29	-0.23
M7 POW	-1.36	-0.35	-0.36	2.91	-0.13
M7M	0.74	-0.35	-0.36	-0.34	-0.13
Mars	-1.36	-0.35	2.75	-0.34	-0.13
Momentum	0.74	-0.35	-0.36	-0.34	-0.13
Multiple	-0.40	1.10	-0.61	0.35	-0.53
N/A	-14.72	5.51	7.68	8.63	1.34
NeoScrypt	1.34	-1.00	0.07	-0.97	-0.38
NIST5	0.60	-1.00	1.18	-0.97	-0.38
Ouroboros	-1.36	-0.35	-0.36	-0.34	**7.42**
Pascal	-1.36	-0.35	2.75	-0.34	-0.13
PHI1612	-0.44	1.75	-0.51	-0.49	-0.19
PoS	2.45	-0.06	-1.73	-1.58	-0.83
POS 2.0	0.74	-0.35	-0.36	-0.34	-0.13
POS 3.0	-0.62	-0.71	0.83	0.94	-0.27
Progressive-n	0.74	-0.35	-0.36	-0.34	-0.13
Proof-of-BibleHash	-1.36	2.83	-0.36	-0.34	-0.13
Quark	1.64	-1.33	-0.53	-0.42	-0.51
QuBit	1.81	-0.87	-0.89	-0.84	-0.33
Scrypt	**7.58**	-2.54	-3.05	-5.06	-2.16
Scrypt-n	1.81	-0.87	-0.89	-0.84	-0.33
ScryptOG	-1.36	2.83	-0.36	-0.34	-0.13
SHA-256	-1.63	1.25	0.07	0.18	2.30
SHA-512	0.74	-0.35	-0.36	-0.34	-0.13
SHA256	**3.58**	-1.64	-2.14	-1.52	-0.30
SHA256D	2.21	-0.48	-1.37	-1.29	-0.51
SHA3	-0.44	-0.50	-0.51	1.82	-0.19
Shabal256	-1.36	-0.35	2.75	-0.34	-0.13
Skein	1.28	-0.61	-0.63	-0.60	-0.23
SkunkHash	0.74	-0.35	-0.36	-0.34	-0.13
SkunkHash v2 Raptor	0.74	-0.35	-0.36	-0.34	-0.13
Stanford Folding	-1.36	2.83	-0.36	-0.34	-0.13
Time Travel	-0.44	-0.50	1.69	-0.49	-0.19
VeChainThor Authority	-1.36	-0.35	-0.36	2.91	-0.13
Whirlpool	0.74	-0.35	-0.36	-0.34	-0.13
X11	**6.65**	-2.34	-3.68	-3.72	-0.87
X11Evo	0.74	-0.35	-0.36	-0.34	-0.13
X11GOST	-1.36	2.83	-0.36	-0.34	-0.13
X13	2.71	-1.76	-0.34	-1.68	-0.87
X14	0.74	-0.35	-0.36	-0.34	-0.13
X15	1.51	0.00	-1.09	-1.03	-0.41
XEVAN	0.74	-0.35	-0.36	-0.34	-0.13
XG Hash	0.74	-0.35	-0.36	-0.34	-0.13

Table 12 *Encrypted algorithm - Market cap* Standardized Person's residuals

	Cl.1	Cl.2	Cl.3	Cl.4	Cl.5
K-means	0.63	0.34	0.18		
Hist DAWass	0.27	0.86	0.16	0.45	0.62
TADPole	0.18	0.26	0.27		

Table 13 Heavy-tail cryptocurrencies, percentage of allocation on the clusters

	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N
1	007	1	365					BIC		366	17.6243	1.1755	3.2589	0.1753	CJ	200	166	3.1078	0.1257	5.0557	0.4399
2	1337	267	99	4.6784	0.2308	3.1925	0.2072	BIGUP	212	154	5.1403	0.2497	4.3769	0.3540	CJC	88	278	7.9498	0.3797	8.1536	1.2848
3	1CR		366	3.1808	0.1542	3.2554	0.1751	BILL	106	260	3.5035	0.1370	3.5268	0.4467	CKC		366	17.3848	1.1615	3.3329	0.1805
4	1ST	365	1	2.3749	0.1011	3.6957	0.2004	BIO	333	33	3.4302	0.1646	3.2460	0.1846	CLAM	85	281	2.1632	0.0820	2.0446	0.0813
5	1WO	74	292	1.8122	0.0611	1.8961	0.0652	BIOB	86	280	5.9623	0.2715	6.2660	0.9309	CLD	279	87	1.5697	0.0380	1.4802	0.0404
6	2015	69	297	2.1282	0.0612	5.4682	0.8763	BIOS	178	188	2.3139	0.0929	2.0955	0.0850	CLICK	95	271	2.9417	0.3669	2.7744	0.0965
7	2BACCO	148	218	1.6282	0.0439	1.6574	0.0518	BIPC	265	101	4.4162	0.2410	3.2113	0.1721	CLINT	77	289	2.8838	0.1020	2.4290	0.2858
8	2GIVE	366		2.4278	0.1022	3.0640	0.1578	BIS	346	20	2.2119	0.0914	2.2243	0.0888	CLOAK	366		3.9675	0.2159	3.9061	0.2184
9	300	275	91	1.7354	0.0554	2.2747	0.0925	BIT	169	197	3.9119	0.1933	3.0439	0.1734	CLR		366	17.7909	1.1873	3.3758	0.1844
10	32BIT	1	365					BIT16	139	227	2.2564	0.0888	2.7775	0.1380	CLUB	247	119	2.8554	0.1148	3.6173	0.2554
11	365	10	356					BITB	366		3.3003	0.1660	2.3790	0.1045	CLUD	93	273	8.4376	0.4132	5.5561	0.7030
12	404	148	218	8.0539	0.4006	2.6170	0.2161	BITOK	318	48	4.8884	0.2553	9.2627	0.7138	CLV		366				
13	42	364	2	4.3206	0.2489	3.2916	0.1671	BITS	90	276	4.2635	0.1799	6.0417	0.8289	CMC	7	359				
14	611	25	341					BITUSD	366		2.3779	0.0880	2.5765	0.1433	CMP	100	266	1.9921	0.0724	6.3787	0.4032
15	808	227	139	2.1440	0.0811	2.0570	0.0818	BITZ	5	361					CMPCO	365	1	4.4033	0.2551	3.7603	0.2013
16	888	134	232	3.6563	0.1476	2.2782	0.1972	BKC		366	3.1792	0.1541	3.2850	0.1774	CMS	264	102	2.7418	0.1115	2.2240	0.1108
17	8BIT	334	32	1.7509	0.0541	1.8518	0.0648	BLAS		366	17.3513	1.1562	3.2644	0.1758	CMT	366		1.9866	0.0746	2.1336	0.0820
18	ABC	9	357					BLAZR	302	64	1.9965	0.0739	3.1079	0.1554	CMTC	177	189	4.1052	0.1805	2.6791	0.2007
19	ABY	366		3.7879	0.2023	3.9318	0.2210	BLC	33	333	1.8852	0.0468	1.5239	0.1852	CNBC		366	17.3005	1.1526	3.3510	0.1825
20	AC	313	53	2.4133	0.1050	4.4097	0.2507	BLITZ	139	227	2.7773	0.1172	2.4628	0.1254	CNC		366	17.7296	1.1830	3.3971	0.1860
21	ACC	331	35	2.0896	0.0817	3.3651	0.1725	BLK	366		3.2968	0.1649	4.4746	0.2649	CND	366		3.0660	0.1562	4.9377	0.2849
22	ACC*	291	75	2.5596	0.1117	2.5694	0.1200	BLOCK	366		4.9149	0.2789	2.3494	0.1038	CNL		366	3.2142	0.1566	3.3792	0.1847
23	ACES	145	221	3.1295	0.1206	4.0567	0.4160	BLRY	141	225	2.3541	0.0915	2.0820	0.0892	CNMT		366	1.9145	0.0639	3.4249	0.1911
24	ACH		366	3.2371	0.1582	3.3896	0.1855	BLU	244	122	2.9784	0.1234	2.8934	0.1814	CNO	329	37	3.2748	0.1637	4.9823	0.3028
25	ACID	109	257	2.7239	0.0956	3.6475	0.4135	BLX	113	253	2.0769	0.0769	2.0525	0.0807	CNT	337	29	2.7084	0.1277	2.0794	0.0789
26	ACN		366					BM	6	360					CNX	147	219	3.2615	0.1293	2.9076	0.2463
27	ACOIN	69	297	3.0579	0.1108	2.8390	0.4013	BMC	366		3.2988	0.1713	2.0589	0.0776	COAL	297	69	3.0754	0.1510	3.8122	0.2114
28	ACP	119	247	2.5229	0.0849	2.2654	0.1908	BNB*	96	270	2.3640	0.0770	3.5575	0.3547	COB	219	147	2.9445	0.1400	1.8385	0.0638
29	ADA	326	40	3.5476	0.1824	7.8722	0.5255	BNC	272	94	1.9359	0.0690	4.5800	0.2654	COC	4	362				
30	ADC	132	234	7.6750	0.3749	5.4270	0.6324	BNT	366		5.2378	0.3074	3.4386	0.1838	COE		366				
31	ADCN	305	61	1.5760	0.0396	1.5118	0.0412	BNX	272	94	3.1675	0.1518	3.2517	0.1769	COIN	85	281	1.7096	0.1235	2.3354	0.0732
32	ADL	113	253	3.3537	0.1316	2.3849	0.2042	BOAT	172	194	2.7200	0.1251	3.0840	0.1566	COLX	320	46	2.6098	0.1261	3.6955	0.1892
33	ADN		366	17.1788	1.1412	3.2603	0.1760	BOB	366		2.3313	0.0990	2.4361	0.1056	COMM		366	17.1159	1.1396	3.4380	0.1892
34	ADST	365	1	2.9568	0.1463	2.4323	0.1047	BOLI	10	356					COMP	182	184	7.3618	0.3704	4.7645	0.4468
35	ADT	366		2.8627	0.1429	2.2766	0.0912	BOMB	118	248	4.0848	0.1735	3.9420	0.4161	CON	54	312	4.1432	0.1690	2.4129	0.3159
36	ADX	366		3.2289	0.1675	3.5632	0.1864	BON	152	214	3.2219	0.1244	3.4182	0.3527	COOL		366	3.2115	0.1564	3.3808	0.1848
37	ADZ	356	10	3.3111	0.1708	3.5878	0.1913	BOSON	231	135	2.2588	0.0943	3.2952	0.1674	COR	308	58	3.9052	0.2091	3.0733	0.1576
38	AE	366		4.2636	0.2393	6.4982	0.4098	BOSS	33	333	9.2133	0.4359	1.7511	0.2265	CORAL	81	285	2.4380	0.0779	3.1794	0.4359
39	AEC	139	227	1.7443	0.0574	1.8704	0.0619	BOST	14	352					CORE	7	359	3.2200	0.1445	2.8622	0.1633
40	AEON	366		4.6230	0.2588	3.6646	0.2044	BPL	314	52	3.7426	0.2044	2.0669	0.0782	COV	366		3.2707	0.1707	3.2404	0.1630
41	AERO		366	3.2124	0.1572	3.2909	0.1767	BQ	53	313	1.6668	0.0359	2.4497	0.3164	COVAL	366		3.1235	0.1578	4.1888	0.2344
42	AGRS	70	296	3.5568	0.1790	3.8056	0.2204	BQC		366	3.2375	0.1582	3.3896	0.1855	COX	185	181	3.4674	0.1472	5.7468	0.5149
43	AGS		366	17.5597	1.1709	3.3789	0.1846	BRAIN	91	275	3.6684	0.1445	3.3178	0.4636	CPAY	354	12	3.9825	0.2193	3.8943	0.2151
44	AHT	206	160	1.5248	0.0368	2.1052	0.0866	BRC		366	17.3513	1.1562	3.2646	0.1758	CPC	328	38	2.0902	0.0808	2.0603	0.0782
45	AIB	336	30	2.5716	0.1198	2.8439	0.1324	BRDD	156	210	3.1763	0.1520	3.1168	0.1668	CPN	298	68	2.8876	0.1369	3.5116	0.1893
46	AIR	328	38	2.3742	0.1008	4.3917	0.2528	BRIT	18	348					CQST	306	60	2.8424	0.1381	2.9888	0.1450
47	ALC	158	208	1.5814	0.0413	1.5694	0.0439	BRK	366		3.4389	0.1818	10.6880	0.7104	CRAB	61	305	2.0081	0.0544	2.3480	0.2874
48	ALEX	4	362					BRO	345	21	3.1684	0.1545	3.5924	0.1994	CRACK		366	3.1797	0.1541	3.4056	0.1867
49	ALF		366	17.5410	1.1785	3.2448	0.1727	BRONZ	3	363					CRAFT	71	295	2.3836	0.0920	2.1012	0.0931
50	ALIS	71	295	5.0383	0.2206	5.4118	0.7924	BRX	366		3.4338	0.1895	5.5173	0.3186	CRAIG		366	17.7093	1.1815	3.2884	0.1776
51	ALN		366	17.3853	1.1557	3.3821	0.1854	BS	90	276	3.5768	0.1416	3.2166	0.3747	CJ	200	166	3.1078	0.1257	5.0557	0.4399
52	ALT	72	294	2.4714	0.0812	2.2377	0.2008	BSC	67	299	2.2665	0.0850	1.8335	0.0695	CJC	88	278	7.9498	0.3797	8.1536	1.2848
53	ALTCOM	298	68	2.8202	0.1238	3.3861	0.1948	BSD	366		6.7992	0.4335	3.6762	0.1957	CKC		366	17.3848	1.1615	3.3329	0.1805
54	ALTOCAR	14	352	2.7999	0.1184	2.3321	0.1146	BST	2	364					CLAM	85	281	2.1632	0.0820	2.0446	0.0813
55	AM	1	365					BSTAR	157	209	5.4248	0.2538	7.4315	0.8168	CLD	279	87	1.5697	0.0380	1.4802	0.0404
56	AMB	366		3.8997	0.2104	3.7684	0.2087	BSTK	47	319	2.1344	0.0606	3.9558	0.7632	CLICK	95	271	2.9417	0.3669	2.7744	0.0965
57	AMBER	92	274	3.8488	0.1552	4.9419	0.7320	BSTY	7	359					CLINT	77	289	2.8838	0.1020	2.4290	0.2858
58	AMC		366	17.8368	1.1905	3.3762	0.1844	BT1	1	365					CLOAK	366		3.9675	0.2159	3.9061	0.2184
59	AMIS	206	160	1.3217	0.0236	1.3503	0.0261	BT2	1	365					CLR		366	17.7909	1.1873	3.3758	0.1844
60	AMM	357	9	3.3020	0.1771	3.4523	0.1747	BTA	364	2	2.5761	0.1171	3.1919	0.1612	CLUB	247	119	2.8554	0.1148	3.6173	0.2554
61	AMP	366		4.2880	0.2319	3.5742	0.2004	BTB	365	1	2.1977	0.0893	4.5224	0.2583	CLUD	93	273	8.4376	0.4132	5.5561	0.7030
62	AMS	134	232	8.3179	0.4130	6.9576	0.8262	BTC	366		17.3356	1.1551	3.3814	0.1848	CLV		366				
63	AMX		366	17.3513	1.1562	3.2646	0.1758	BTCA	254	112	1.6797	0.0437	2.0036	0.0901	CMC	7	359				
64	AMY	100	266	1.8773	0.0605	2.0315	0.0826	BTCD	269	97	2.7247	0.1213	2.1861	0.0926	CMP	100	266	1.9921	0.0724	6.3787	0.4032
65	ANAL	193	173	2.0161	0.0730	2.2899	0.0984	BTCE	84	282	1.7951	0.0540	1.7447	0.0610	CMPCO	365	1	4.4033	0.2551	3.7603	0.2013
66	ANC		366	3.2389	0.1583	3.3762	0.1844	BTCM	330	36	3.0593	0.1486	3.3788	0.1803	CMS	264	102	2.7418	0.1115	2.2240	0.1108
67	AND		366					BTCR	273	93	2.6202	0.1188	2.7202	0.1282	CMT	366		1.9866	0.0746	2.1336	0.0820
68	ANGL	25	341	2.2046	0.0831	1.9628	0.0771	BTCRED	301	65	3.4561	0.1585	3.6976	0.2403	CMTC	177	189	4.1052	0.1805	2.6791	0.2007
69	ANI	366		2.7336	0.1354	2.7108	0.1204	BTCRY	209	157	4.4899	0.2078	2.6905	0.1845	CNBC		366	17.3005	1.1526	3.3510	0.1825
70	ANT	366		3.9168	0.2133	4.3629	0.2514	BTCS	122	244	3.6001	0.1484	1.8035	0.1046	CNC		366	17.7296	1.1830	3.3971	0.1860
71	ANTI	87	279	4.1914	0.1721	4.3382	0.7117	BTCZ	349	17	3.8227	0.2064	3.4416	0.1825	CND	366		3.0660	0.1562	4.9377	0.2849
72	APC	313	53	3.1303	0.1541	2.9661	0.1486	BTD	158	208	2.7158	0.0965	3.1668	0.3064	CNL		366	3.2142	0.1566	3.3792	0.1847
73	APEX		366	17.2295	1.1476	3.2779	0.1768	BTDX	179	187	2.1277	0.0773	3.1931	0.1773	CNMT		366	1.9145	0.0639	3.4249	0.1911
74	APT	301	65	4.2786	0.2360	2.3921	0.1058	BTE		366	3.1992	0.1559	3.3563	0.1823	CNO	329	37	3.2748	0.1637	4.9823	0.3028
75	APX	342	24	6.9617	0.4325	2.7867	0.1347	BTG	366		3.7226	0.2024	5.2882	0.3153	CNT	337	29	2.7084	0.1277	2.0794	0.0789
76	AQUA		366	3.2543	0.1590	3.4351	0.1896	BTH	183	183	3.3747	0.1355	2.5738	0.2049	CNX	147	219	3.2615	0.1293	2.9076	0.2463
77	ARB	109	257	2.8063	0.1343	1.7543	0.0555	BTLC	8	358					COAL	297	69	3.0754	0.1510	3.8122	0.2114
78	ARC		366					BTM	366		2.6383	0.1153	2.7262	0.1348	COB	219	147	2.9445	0.1400	1.8385	0.0638
79	ARC*	134	232	2.5500	0.0896	2.7047	0.2083	BTM*	366		3.1186	0.1558	6.6960	0.4234	COC	4	362				
80	ARCH		366	17.7345	1.1833	3.3795	0.1847	BTMI		366	17.3513	1.1562	3.2646	0.1758	COE		366				
81	ARCO	8	358					BTPL		366	17.2312	1.1477	3.3845	0.1851	COIN	85	281	1.7096	0.1235	2.3354	0.0732
82	ARDR	366		2.9893	0.1443	4.2898	0.2480	BTQ	274	92	2.7796	0.1301	1.9065	0.0678	COLX	320	46	2.6098	0.1261	3.6955	0.1892
83	ARENA	3	363	3.3587	0.1660	2.8737	0.1463	BTSE	10	356	3.2942	0.1576	2.4085	0.1135	COMM		366	17.1159	1.1396	3.4380	0.1892
84	ARG	337	29	3.2045	0.1776	2.3995	0.0961	BTTF	5	361					COMP	182	184	7.3618	0.3704	4.7645	0.4468
85	ARGUS	71	295	2.6901	0.0926	3.5429	0.4427	BTU		366	17.3566	1.1566	3.3842	0.1850	CON	54	312	4.1432	0.1690	2.4129	0.3159
86	ARI	363	3	2.9805	0.1452	2.3729	0.1023	BTX	366		4.0402	0.2247	4.0200	0.2232	COOL		366	3.2115	0.1564	3.3808	0.1848
87	ARK	366		5.4212	0.3233	2.7702	0.1323	BTXC	116	250	3.0726	0.1382	2.2144	0.1023	COR	308	58	3.9052	0.2091	3.0733	0.1576
88	ARM	169	197	2.6120	0.0913	2.9191	0.2612	BTZ	172	194	2.0474	0.0752	1.9348	0.0713	CORAL	81	285	2.4380	0.0779	3.1794	0.4359
89	ARN	366		2.9687	0.1528	4.0328	0.2145	BUCKS	78	288	2.1420	0.0629	2.9851	0.3309	CORE	7	359	3.2200	0.1445	2.8622	0.1633
90	ARPA	160	206	2.1951	0.0841	1.8958	0.0699	BUK		366	20.8391	1.4244	3.5298	0.1929	COV	366		3.2707	0.1707	3.2404	0.1630
91	ART	352	14	2.9224	0.1413	4.4017	0.2528	BUN	50	316	17.3513	1.1562	3.2646	0.1758	COVAL	366		3.1235	0.1578	4.1888	0.2344
92	ARTE	249	117	1.6706	0.0463	4.6001	0.2882	BURST	366		4.1995	0.2327	2.4163	0.1065	COX	185	181	3.4674	0.1472	5.7468	0.5149
93	ASAFE2	239	127	4.1651	0.2977	5.5153	0.2839	BUZZ	294	72	7.7257	0.4271	4.3118	0.3049	CPAY	354	12	3.9825	0.2193	3.8943	0.2151
94	ASN	75	291	8.9298	0.4313	3.0923	0.3954	BVC	62	304	3.8287	0.1523	2.8325	0.3999	CPC	328	38	2.0902	0.0808	2.0603	0.0782
95	AST	366		3.2783	0.1666	4.7953	0.2837	BWK	360	6	4.3581	0.2393	3.2869	0.1759	CPN	298	68	2.8876	0.1369	3.5116	0.1893
96	AST*	221	145	3.1399	0.1509	3.7805	0.2165	BXC	157	209	2.0290	0.0873	2.3711	0.0910	CQST	306	60	2.8424	0.1381	2.9888	0.1450
97	ASTRO	270	96	3.0067	0.1464	2.4057	0.1054	BXT	112	254	3.0280	0.3207	3.1197	0.1174	CRAB	61	305	2.0081	0.0544	2.3480	0.2874
98	ATB	256	110	2.2089	0.0784	2.5090	0.1334	BYC	293	73	2.6942	0.1186	2.2913	0.1015	CRACK		366	3.1797	0.1541	3.4056	0.1867
99	ATCC	43	323	2.6628	0.1094	2.4715	0.1266	C2	61	305	3.2523	0.1216	2.9011	0.3964	CRAFT	71	295	2.3836	0.0920	2.1012	0.0931
100	ATL	363	3	3.5780	0.1895	5.0531	0.3013	CAB	197	169	2.4794	0.0861	2.5286	0.1814	CRAIG		366	17.7093	1.1815	3.2884	0.1776
101	ATM*	119	247	8.9582	0.4491	7.4141	0.8895	CACH	270	96	2.8636	0.1335	4.1584	0.2415	CJ	200	166	3.1078	0.1257	5.0557	0.4399
102	ATOM	118	248	2.3896	0.0781	2.5303	0.2186	CAG	366		2.6031	0.1309	2.5129	0.1029	CJC	88	278	7.9498	0.3797	8.1536	1.2848
103	ATS	315	51	4.3711	0.2420	8.8058	0.5952	CAID	6	360					CKC		366	17.3848	1.1615	3.3329	0.1805
104	ATT	1	365	9.3342	0.5984	3.2064	0.1682	CAIX		366	17.1882	1.1447	3.2472	0.1744	CLAM	85	281	2.1632	0.0820	2.0446	0.0813
105	ATX	268	98	1.9742	0.0741	2.1086	0.0798	CALC	15	351					CLD	279	87	1.5697	0.0380	1.4802	0.0404
106	AUA	81	285	2.2886	0.0883	2.0511	0.0850	CAM	31	335	2.4930	0.1295	3.3199	0.1520	CLICK	95	271	2.9417	0.3669	2.7744	0.0965
107	AUD	366		4.3176	0.2466	2.9069	0.1402	CAN	348	18	2.3318	0.0966	2.2669	0.0955	CLINT	77	289	2.8838	0.1020	2.4290	0.2858
108	AUR	120	246	2.7650	0.0981	2.7677	0.2728	CANN	366		3.9230	0.2137	3.4635	0.1841	CLOAK	366		3.9675	0.2159	3.9061	0.2184
109	AURS		366					CAP	204	162	1.5891	0.0409	1.8848	0.0702	CLR		366	17.7909	1.1873	3.3758	0.1844
110	AV	254	112	3.1068	0.1570	3.6697	0.1958	CAPP	310	56	2.5175	0.1122	3.4651	0.1822	CLUB	247	119	2.8554	0.1148	3.6173	0.2554
111	AVT	348	18	3.4647	0.1743	5.7222	0.3665	CARBON	305	61	3.5657	0.1730	4.0327	0.2510	CLUD	93	273	8.4376	0.4132	5.5561	0.7030
112	AXIOM	3	363					CASH		366	3.1588	0.1527	3.3867	0.1852	CLV		366				
113	AXR		366	3.2193	0.1569	3.3673	0.1837	CAT*	219	147	2.7938	0.1115	2.8986	0.1835	CMC	7	359				
114	B2B	306	60	3.2497	0.1632	2.5329	0.1155	CBC	188	178	2.6171	0.1489	4.7222	0.2364	CMP	100	266	1.9921	0.0724	6.3787	0.4032
115	B2X	366		1.6516	0.0469	1.6629	0.0504	CBD	6	360					CMPCO	365	1	4.4033	0.2551	3.7603	0.2013
116	B3	270	96	3.5782	0.1631	3.1264	0.1974	CBX	8	358					CMS	264	102	2.7418	0.1115	2.2240	0.1108
117	BAC	84	282	5.0891	0.2218	2.5485	0.3037	CC	113	253	3.3962	0.1329	4.5236	0.5503	CMT	366		1.9866	0.0746	2.1336	0.0820
118	BAN	131	235	1.6963	0.0502	1.7373	0.0559	CCC	188	178	4.7837	0.2226	4.7454	0.4268	CMTC	177	189	4.1052	0.1805	2.6791	0.2007
119	BAR	39	327	2.2371	0.1098	2.7212	0.1113	CCN	263	103	3.2725	0.1568	2.9449	0.1557	CNBC		366	17.3005	1.1526	3.3510	0.1825
120	BAS	313	53	3.6255	0.1936	3.8718	0.2129	CCO	144	222	1.7454	0.0541	4.7078	0.2795	CNC		366	17.7296	1.1830	3.3971	0.1860
121	BASH	130	236	3.4323	0.1353	3.0419	0.3114	CCRB	199	167	2.0207	0.0598	2.0392	0.1200	CND	366		3.0660	0.1562	4.9377	0.2849
122	BAT	366		4.2004	0.2353	4.0480	0.2266	CCT	342	24	2.7815	0.1310	2.2688	0.0943	CNL		366	3.2142	0.1566	3.3792	0.1847
123	BAY	366		4.2425	0.2359	3.7831	0.2092	CCX	86	280	4.2459	0.1760	3.2078	0.4330	CNMT		366	1.9145	0.0639	3.4249	0.1911
124	BBCC	82	284	3.1233	0.1157	6.3280	0.9894	CDN	366		3.9352	0.2194	4.1358	0.2293	CNO	329	37	3.2748	0.1637	4.9823	0.3028
125	BBP	332	34	3.0909	0.1537	3.6063	0.1937	CDT	366		4.9799	0.2918	4.6730	0.2738	CNT	337	29	2.7084	0.1277	2.0794	0.0789
126	BBR	89	277	3.5773	0.1905	5.2597	0.3149	CDX	303	63	2.4218	0.1029	2.6164	0.1222	CNX	147	219	3.2615	0.1293	2.9076	0.2463
127	BBT	92	274	4.0867	0.1707	2.9998	0.3202	CDY	35	331	3.1232	0.1330	2.2352	0.1172	COAL	297	69	3.0754	0.1510	3.8122	0.2114
128	BC		366	3.2330	0.1587	3.3681	0.1827	CEFS	365	1	3.1554	0.1611	3.4122	0.1764	COB	219	147	2.9445	0.1400	1.8385	0.0638
129	BCAP		366	18.8255	1.2605	3.3108	0.1793	CELL		366					COC	4	362				
130	BCCOIN	67	299	2.0830	0.0601	2.2847	0.2006	CESC	23	343	4.1238	0.9018	2.2043	0.0640	COE		366				
131	BCD	366		1.8003	0.0605	1.8552	0.0619	CETI		366	16.8557	1.1212	3.3739	0.1843	COIN	85	281	1.7096	0.1235	2.3354	0.0732
132	BCDN	339	27	3.4587	0.1822	4.2419	0.2390	CF	113	253	3.5091	0.1409	6.1714	0.7388	COLX	320	46	2.6098	0.1261	3.6955	0.1892
133	BCH	366		5.1412	0.3053	2.4633	0.1085	CFC	102	264	3.7021	0.1481	2.5816	0.2753	COMM		366	17.1159	1.1396	3.4380	0.1892
134	BCN	366		2.9979	0.1469	5.4547	0.3311	CFT	87	279	2.4151	0.0948	2.7949	0.1501	COMP	182	184	7.3618	0.3704	4.7645	0.4468
135	BCOIN		366	3.2121	0.1564	3.3550	0.1828	CGA		366	17.4736	1.1678	3.2542	0.1744	CON	54	312	4.1432	0.1690	2.4129	0.3159
136	BCPT	366		3.5577	0.1928	3.2923	0.1663	CGT		366	17.1159	1.1396	3.4380	0.1892	COOL		366	3.2115	0.1564	3.3808	0.1848
137	BCR		366	17.1475	1.1418	3.3706	0.1840	CHA		366	3.1987	0.1555	3.4040	0.1866	COR	308	58	3.9052	0.2091	3.0733	0.1576
138	BCX	160	206	2.1862	0.0856	2.5016	0.1138	CHAO		366	17.3355	1.1551	3.3814	0.1848	CORAL	81	285	2.4380	0.0779	3.1794	0.4359
139	BCY	360	6	2.3030	0.0961	2.0223	0.0758	CHASH		366	17.6408	1.1767	3.2625	0.1756	CORE	7	359	3.2200	0.1445	2.8622	0.1633
140	BDL	9	357					CHAT	363	3	2.2807	0.0944	2.6326	0.1210	COV	366		3.2707	0.1707	3.2404	0.1630
141	BDT	366		3.9357	0.2213	4.2603	0.2365	CHC		366					COVAL	366		3.1235	0.1578	4.1888	0.2344
142	BELA	140	226	3.5615	0.1719	3.4789	0.2066	CHESS	10	356					COX	185	181	3.4674	0.1472	5.7468	0.5149
143	BENJI	101	265	1.8871	0.0480	2.1506	0.2301	CHIEF		366	17.3513	1.1562	3.2646	0.1758	CPAY	354	12	3.9825	0.2193	3.8943	0.2151
144	BERN	139	227	4.4302	0.1933	4.3604	0.4706	CHILD		366	17.4880	1.1659	3.2646	0.1758	CPC	328	38	2.0902	0.0808	2.0603	0.0782
145	BEST	104	262	1.8252	0.0460	2.5051	0.2269	CHIP	56	310	2.6326	0.0880	2.7173	0.3661	CPN	298	68	2.8876	0.1369	3.5116	0.1893
146	BET		366	17.1943	1.1480	3.2767	0.1762	CHOOF	98	268	3.1696	0.1202	4.4799	0.5502	CQST	306	60	2.8424	0.1381	2.9888	0.1450
147	BET*	364	2	3.6642	0.1948	3.2386	0.1673	CIN	145	221	1.9776	0.0711	3.2382	0.1682	CRAB	61	305	2.0081	0.0544	2.3480	0.2874
148	BFX		366					CINNI		366	3.2176	0.1568	3.4052	0.1867	CRACK		366	3.1797	0.1541	3.4056	0.1867
149	BHC		366	3.2193	0.1569	3.3740	0.1843	CIR		366	17.3513	1.1562	3.2646	0.1758	CRAFT	71	295	2.3836	0.0920	2.1012	0.0931
150	BHC*	79	287	2.7273	0.0938	2.7780	0.3422	CIRC	5	361					CRAIG		366	17.7093	1.1815	3.2884	0.1776

Table 14 Summary-list of the cryptocurrencies considered on the market analysis along 2018 (part 1 out of 5)

	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N
151	CRAVE	4	362					EGG	2	364					GHOUL		366				
152	CRB	323	43	3.5527	0.1823	2.4104	0.1082	EGO	90	276	1.9916	0.0721	2.0071	0.0757	GIFT	155	211	3.6036	0.1841	2.2061	0.0936
153	CRE	3	363					EKN		366					GIG	112	254	2.1438	0.0807	3.7168	0.2115
154	CREA	365	1	3.7853	0.2048	3.7345	0.2033	EKO	358	8	2.4857	0.1260	3.1982	0.1459	GIM	101	265	1.9290	0.0652	1.8589	0.0673
155	CRED	218	148	1.6703	0.0457	1.8224	0.0669	ELC	3	363					GIN	189	177	2.5388	0.1240	4.9526	0.2715
156	CREDO	217	149	4.5326	0.2670	1.7929	0.0574	ELE	109	257	3.3279	0.1303	2.7450	0.2545	GIVE		366	3.2371	0.1582	3.3896	0.1855
157	CREVA	176	190	1.8830	0.0626	3.3937	0.1852	ELITE	275	91	3.8637	0.1665	1.7584	0.0906	GIZ	8	358				
158	CRM	8	358					ELIX	366		4.1404	0.2430	3.9500	0.2091	GLC	121	245	2.8220	0.1022	12.7945	1.7024
159	CRPS	137	229	1.8566	0.0606	1.9325	0.0724	ELLA	365	1	3.2144	0.1646	9.6113	0.6331	GLD	366		3.4457	0.1876	2.5792	0.1128
160	CRTM	66	300	1.8692	0.0590	1.7138	0.0585	ELM	5	361					GLOBE		366	17.3513	1.1562	3.2646	0.1758
161	CRW	366		3.5985	0.1921	3.9410	0.2174	ELP	265	101	2.7552	0.1319	1.8334	0.0606	GLT		366	17.3027	1.1528	3.4022	0.1864
162	CRX	127	239	3.7271	0.1544	5.1096	0.5592	ELS		366	3.2067	0.1560	3.3692	0.1839	GLX		366	3.2047	0.1559	3.3855	0.1852
163	CRYPT	41	325	4.3158	0.2241	2.6517	0.1362	ELTC2	31	335	2.2604	0.0914	2.3982	0.1054	GLYPH		366	19.5093	1.3023	3.2641	0.1768
164	CS	120	246	3.5074	0.1406	3.2004	0.3176	ELTCOIN	136	230	1.7207	0.0503	2.1801	0.0930	GMC		366				
165	CSC	106	260	2.5077	0.0944	2.7532	0.1664	EMB	233	133	5.3407	0.2627	4.9905	0.4138	GML	60	306	1.7708	0.0413	3.9044	0.7044
166	CSH		366					EMC	366		3.3945	0.1810	3.5596	0.1852	GMX	37	329	2.8848	0.1005	1.9455	0.2527
167	CSMIC	1	365					EMC2	366		3.5072	0.1833	6.8833	0.4397	GNJ		366				
168	CSNO	354	12	3.4536	0.1804	6.5587	0.4132	EMD	312	54	3.1947	0.1564	3.8996	0.2230	GNO	366		4.7225	0.2729	4.2857	0.2449
169	CST	164	202	1.8470	0.0618	2.1118	0.0833	EMPC	5	361					GNT	366		3.1522	0.1553	5.8534	0.3679
170	CTC		366					EMV	125	241	1.7795	0.0579	1.8758	0.0644	GOAT	38	328	3.4197	0.1281	7.8831	2.2944
171	CTIC	2	364					ENE	150	216	1.9379	0.0658	1.8999	0.0705	GOLOS	366		2.4932	0.1095	2.3772	0.1026
172	CTO	16	350					ENG	366		3.5254	0.1832	2.3306	0.1003	GOOD	8	358	2.3361	0.0950	2.5947	0.1230
173	CTR	153	213	4.9841	0.2308	2.9608	0.2378	ENJ	366		2.2292	0.0909	2.4259	0.1054	GOON	150	216	1.7489	0.0519	1.7674	0.0610
174	CTT	44	322	2.3549	0.0924	2.1724	0.0954	ENRG	300	66	3.4594	0.1757	3.4187	0.1855	GOT	117	249	5.0390	0.2244	4.2824	0.5065
175	CTX	351	15	2.2049	0.0881	2.3336	0.0997	ENT	353	13	1.7863	0.0569	3.4214	0.1830	GOTX	152	214	1.6879	0.0393	5.8950	0.6373
176	CUBE	5	361					ENTER	97	269	3.3334	0.1288	5.2898	0.6959	GP	5	361				
177	CURE	366		5.6659	0.3459	2.3956	0.1029	ENTRC	15	351	2.6781	0.1057	1.9029	0.0846	GPL	273	93	4.6758	0.2593	3.0698	0.1611
178	CVC	366		3.3756	0.1714	5.5530	0.3452	EOC	178	188	2.1452	0.0820	5.3679	0.3340	GPU	159	207	4.8221	0.2174	2.2073	0.1599
179	CWV	211	155	2.0915	0.0832	5.1499	0.2979	EOS	366		2.9476	0.1424	3.5227	0.1886	GRAM	302	64	2.6668	0.1092	3.1017	0.1822
180	CWXT	214	152	1.6604	0.0461	3.3561	0.1857	EPY	1	365					GRAV	5	361				
181	CXC		366	3.1982	0.1547	3.3431	0.1830	EQ		366	3.1477	0.1519	3.2729	0.1764	GRC	366		4.1780	0.2264	3.6234	0.2018
182	CXT	73	293	1.9194	0.0689	2.0109	0.0737	EQM	2	364					GRE	148	218	4.1504	0.1816	2.6072	0.1993
183	CYC	65	301	4.7144	0.2000	6.2967	1.1558	EQT	2	364					GREXIT	173	193	3.5836	0.1869	2.1772	0.0890
184	CYG	98	268	1.7375	0.0400	2.6737	0.3282	EQUAL	9	357					GRID		366				
185	CYP	4	362					ERC	286	80	6.1071	0.3657	2.3138	0.1005	GRM		366	3.2284	0.1576	3.3018	0.1787
186	CZC		366	3.1856	0.1545	3.3829	0.1849	EREAL	140	226	2.7733	0.1270	1.5719	0.0437	GROW		366				
187	DAI	274	92	1.8714	0.0519	1.7027	0.0767	ERO	353	13	2.4151	0.1032	2.9835	0.1487	GRS	366		2.9696	0.1472	4.0881	0.2258
188	DANK		366	3.2217	0.1567	3.3715	0.1846	ERR	97	269	2.0028	0.0713	2.0239	0.0790	GRW	302	64	3.3438	0.1653	5.3645	0.3398
189	DARK	244	122	3.5896	0.1822	7.0147	0.4697	ERY		366					GRX	226	140	1.7898	0.0540	4.2266	0.2617
190	DAS	15	351					ESP	241	125	3.3885	0.1702	4.6457	0.2804	GSM	2	364				
191	DASH	366		3.3554	0.1722	2.3559	0.1013	EST		366					GSX	2	364				
192	DAT	366		3.9599	0.2225	7.7790	0.4931	ETBS	337	29	2.6057	0.1162	3.0353	0.1539	GSY	134	232	2.1669	0.0787	1.9936	0.0822
193	DATA	366		4.3006	0.2440	3.1756	0.1608	ETBT	30	336	2.3835	0.0929	1.9449	0.0787	GUE		366	17.1052	1.1388	3.2823	0.1771
194	DAXX	316	50	2.1545	0.0829	3.7090	0.2066	ETC	366		4.6969	0.2689	6.4972	0.4132	GUN	296	70	2.2617	0.0935	2.2820	0.0945
195	DAY	305	61	2.9904	0.1475	3.5763	0.1899	ETG	116	250	1.7641	0.0512	1.5914	0.0495	GUNS	1	365	2.6387	0.1123	2.9410	0.1569
196	DB	4	362					ETH	366		9.3143	0.5969	3.1858	0.1667	GUP	366		3.2365	0.1610	3.6725	0.2032
197	DBET	364	2	2.9855	0.1492	4.7186	0.2705	ETHB	12	354	2.4202	0.1036	2.6374	0.1227	GVT	366		3.3465	0.1744	8.3068	0.5372
198	DBG	224	142	2.1608	0.0833	2.4308	0.1091	ETHD	363	3	4.0051	0.2265	3.4985	0.1813	GXC	3	363	3.5428	0.1710	2.5578	0.1294
199	DBIC	71	295	4.9037	0.2142	2.6426	0.2817	ETHOS	349	17	2.3668	0.1005	3.4310	0.1807	GXC*		366	3.2176	0.1568	3.3108	0.1794
200	DBIX	366		2.2985	0.0990	3.6646	0.1913	ETHS	117	249	3.1656	0.1209	3.4405	0.3638	GXS	366		3.6604	0.1967	3.0021	0.1480
201	DBTC	159	207	3.0192	0.1158	3.5581	0.3249	ETL	3	363					H2O	178	188	1.6259	0.0454	1.5397	0.0407
202	DCC	63	303	2.7977	0.4237	2.3855	0.0743	ETN	365	1	2.8577	0.1392	3.3901	0.1743	HAC	4	362				
203	DCK	78	288	3.5430	0.1385	3.1079	0.3914	ETP	366		3.9592	0.2164	2.8746	0.1401	HAL	327	39	2.6414	0.1223	3.4710	0.1812
204	DCN	340	26	3.7507	0.2068	4.0694	0.2233	ETT	336	30	3.8194	0.2119	3.2755	0.1655	HALLO	94	272	2.7164	0.0946	2.6915	0.2781
205	DCR	366		2.4317	0.1033	4.1005	0.2350	EUC	75	291	7.0436	0.3263	1.7968	0.1662	HAMS	64	302	6.1697	0.2808	4.5863	0.6902
206	DCRE	5	361					EVC	316	50	1.9395	0.0721	3.8354	0.2025	HAZE	2	364				
207	DCY	353	13	3.6505	0.1943	6.0855	0.3791	EVENT		366	3.2132	0.1565	3.2921	0.1779	HBN	230	136	3.3003	0.1623	3.2411	0.1745
208	DDF	138	228	1.9936	0.0692	3.7948	0.2210	EVIL	79	287	4.9994	0.2159	6.1123	1.0660	HBT	282	84	2.9642	0.1456	2.8571	0.1369
209	DEA	224	142	2.7254	0.1308	2.3970	0.1008	EVR	129	237	2.1051	0.0638	1.9831	0.1210	HC	365	1	2.5790	0.1281	2.3778	0.0942
210	DEEP	19	347					EVX	366		3.1402	0.1600	2.5287	0.1118	HCC	198	168	3.0119	0.1205	2.5570	0.1669
211	DEM	172	194	11.8288	0.6242	6.4158	0.6718	EXB	250	116	2.9302	0.1447	2.2542	0.0915	HDG	91	275	3.4126	0.1336	2.3523	0.2138
212	DES	6	360					EXC		366	3.1836	0.1544	3.2701	0.1762	HEAT	7	359				
213	DETH	98	268	3.4755	0.1365	3.5514	0.4194	EXCL	366		4.0452	0.2239	3.8147	0.2092	HEX		366	3.6060	0.1901	3.4472	0.1834
214	DEUR		366					EXE		366	17.4638	1.1642	3.3805	0.1848	HILL		366				
215	DFS	6	360	3.3760	0.1628	2.7560	0.1420	EXIT	162	204	5.0786	0.2335	6.0371	0.6449	HIRE	72	294	4.0490	0.6654	6.1812	0.2789
216	DFT	365	1	3.5658	0.1771	5.0238	0.3222	EXN	282	84	1.4958	0.0353	19.0197	1.3861	HKG		366	16.8557	1.1212	3.3739	0.1843
217	DGB	366		4.2018	0.2341	3.6042	0.1946	EXP	366		3.8812	0.2166	3.1322	0.1551	HKN	365	1	3.5802	0.1985	3.9118	0.2075
218	DGC	366		5.7265	0.3503	2.2986	0.0957	EZC		366	17.6705	1.1817	3.3036	0.1783	HLC	120	246	2.0041	0.0730	2.1294	0.0849
219	DGD	366		3.4625	0.1763	4.1177	0.2384	F16	123	243	3.8431	0.1584	3.0202	0.3046	HMC	365	1	2.6788	0.1323	2.7252	0.1205
220	DGDC	164	202	3.0973	0.2730	4.0089	0.1717	FAIR	90	276	3.2429	0.1533	3.4796	0.2011	HMP	195	171	4.5450	0.2146	5.8956	0.5076
221	DGMS	61	305	3.5601	0.1390	2.9471	0.3747	FAME		366	3.1992	0.1559	3.3563	0.1823	HMQ	366		4.1630	0.2242	3.7802	0.2151
222	DGORE	148	218	1.8286	0.0560	1.7182	0.0592	FAZZ	89	277	2.9190	0.1045	3.4604	0.4569	HNC	343	23	3.1936	0.1692	4.4888	0.2479
223	DGPT	235	131	3.0876	0.1451	3.5037	0.1986	FC	53	313	1.7434	0.0588	1.8580	0.0598	HODL	95	271	1.8469	0.0611	1.9286	0.0704
224	DICE	366		3.1992	0.1648	3.5336	0.1848	FC2	126	240	2.5427	0.1062	2.2886	0.1035	HONEY		366	17.4749	1.1679	3.2725	0.1759
225	DIEM	60	306	1.9837	0.0696	1.9239	0.0717	FCN	362	4	1.8797	0.0640	1.9060	0.0681	HPC	365	1	3.6506	0.2004	3.8916	0.2092
226	DIGS		366	3.2371	0.1582	3.3896	0.1855	FCS		366	3.2305	0.1577	3.3928	0.1857	HRB		366	3.7817	0.2008	2.9265	0.1461
227	DIM	335	31	1.7099	0.0491	10.8773	0.7883	FCT	366		3.6637	0.1958	3.6886	0.1998	HSP	133	233	1.8423	0.0599	2.1973	0.0924
228	DIME	364	2	5.6851	0.3408	6.1979	0.3907	FFC	160	206	3.6324	0.1495	8.2498	0.9688	HSR	366		2.3595	0.0994	4.8304	0.2863
229	DISK	187	179	3.1531	0.1519	3.2138	0.1723	FGZ	176	190	1.7224	0.0506	3.8633	0.2250	HST	365	1	2.5277	0.1145	2.7660	0.1288
230	DKC	2	364					FIBRE		366	17.5516	1.1704	3.3746	0.1843	HTC	194	172	12.3213	0.6671	2.7555	0.1988
231	DLC	6	360					FIND	45	321	1.7460	0.0400	3.6924	0.6177	HTML	356	10	2.4693	0.1137	2.7181	0.1218
232	DLISK	154	212	1.6219	0.0442	1.7627	0.0588	FIRE	188	178	1.8795	0.0628	3.6562	0.2037	HTML5	282	84	2.3155	0.0853	2.4561	0.1287
233	DLT	366		2.2200	0.0914	4.8494	0.2807	FIRST		366					HUC	366		3.8633	0.2088	4.1050	0.2327
234	DMD	366		4.0766	0.2300	4.6243	0.2650	FIST	110	256	3.7120	0.1526	4.3236	0.4700	HUGE		366				
235	DNA	365	1	2.4308	0.1091	3.7928	0.2005	FIT	217	149	1.4723	0.0334	5.2284	0.3282	HUSH	345	21	3.1752	0.1644	3.0925	0.1514
236	DNET		366	3.2190	0.1573	3.3983	0.1856	FJC	366		4.7154	0.2688	4.2966	0.2492	HVC		366	3.2132	0.1565	3.2921	0.1779
237	DNR	332	34	3.2981	0.1737	5.4299	0.3205	FLASH	365	1	3.5033	0.1909	2.5095	0.1084	HVCO	3	363				
238	DNT	366		2.3952	0.1061	4.1645	0.2278	FLDC	366		2.5950	0.1122	3.8887	0.2256	HVN	366		3.4068	0.1784	5.6670	0.3441
239	DOC		366	17.7909	1.1873	3.3758	0.1844	FLEX		366	17.3772	1.1580	3.3568	0.1829	HXX	185	181	3.0158	0.2297	2.7257	0.1015
240	DOGE	366		3.0126	0.1530	4.3313	0.2398	FLIK	49	317	1.9939	0.0694	1.9347	0.0737	HYP		366				
241	DOGED		366					FLIXX	366		2.8676	0.1441	2.9289	0.1371	HYPER	7	359	2.2707	0.0927	2.7513	0.1313
242	DOGETH	185	181	4.9047	0.2243	4.5809	0.4512	FLLW	65	301	1.6091	0.0450	1.6037	0.0446	HZ		366	3.2176	0.1568	3.3108	0.1794
243	DON	257	109	3.0834	0.1459	7.5563	0.5151	FLO	366		4.0078	0.2236	3.8697	0.2110	HZT	78	288	1.5882	0.0315	4.7871	0.9185
244	DOPE	366		3.6481	0.1936	3.5452	0.1902	FLT	293	73	3.0956	0.1486	2.3032	0.1008	I0C		366				
245	DOT		366					FLVR	7	359					IBANK	216	150	4.9992	0.2821	2.0294	0.0801
246	DOV	361	5	2.0214	0.0766	4.1036	0.2264	FLX	143	223	1.8259	0.0596	1.9907	0.0751	ICASH	121	245	1.9387	0.0681	1.9178	0.0692
247	DP	366		4.5225	0.2670	3.2857	0.1650	FLY	3	363					ICB		366	18.0224	1.2067	3.2662	0.1754
248	DPAY	127	239	1.9009	0.0629	1.8870	0.0699	FNL	21	345	1.9338	0.0886	2.3764	0.0862	ICE	15	351	2.2781	0.0911	2.2080	0.0929
249	DPP	255	111	3.1254	0.1534	3.2146	0.1679	FNX		366					ICN	366		2.4910	0.1076	6.9066	0.4478
250	DPY	366		4.3347	0.2465	3.3156	0.1712	FONZ	108	258	1.7074	0.0391	3.4085	0.3907	ICOB	72	294	3.8549	0.1553	5.4090	0.8332
251	DRA	194	172	2.7713	0.1282	2.3122	0.0992	FOREX	212	154	3.6269	0.1573	4.3656	0.3608	GHOUL		366				
252	DRACO	1	365					FORK	335	31	2.4918	0.1112	3.8013	0.2054	GIFT	155	211	3.6036	0.1841	2.2061	0.0936
253	DRGN	366		2.1508	0.0870	4.7063	0.2682	FPC	58	308	2.5446	0.0834	2.6118	0.3361	GIG	112	254	2.1438	0.0807	3.7168	0.2115
254	DRKC		366	3.2000	0.1556	3.3824	0.1849	FRAC		366	17.0840	1.1373	3.2975	0.1783	GIM	101	265	1.9290	0.0652	1.8589	0.0673
255	DRKT	5	361					FRAZ		366	3.2305	0.1577	3.3928	0.1857	GIN	189	177	2.5388	0.1240	4.9526	0.2715
256	DRM8	11	355					FRC	15	351	2.5687	0.1173	2.7317	0.1266	GIVE		366	3.2371	0.1582	3.3896	0.1855
257	DROP	281	85	3.8166	0.1845	2.2399	0.1075	FRD	187	179	3.0075	0.1372	2.3182	0.1069	GIZ	8	358				
258	DRP	147	219	2.9429	0.1367	2.8825	0.1470	FRE	113	253	1.4056	0.0224	6.8065	0.9546	GLC	121	245	2.8220	0.1022	12.7945	1.7024
259	DRPU	343	23	3.3258	0.1705	4.0473	0.2271	FRK	106	260	3.6397	0.1458	4.6830	0.5975	GLD	366		3.4457	0.1876	2.5792	0.1128
260	DRT	342	24	3.7819	0.2062	2.9733	0.1455	FRN	6	360					GLOBE		366	17.3513	1.1562	3.2646	0.1758
261	DRXNE	317	49	2.4016	0.1045	3.5835	0.1894	FRST	341	25	2.2564	0.0909	3.8909	0.2185	GLT		366	17.3027	1.1528	3.4022	0.1864
262	DRZ	5	361					FRWC	3	363					GLX		366	3.2047	0.1559	3.3855	0.1852
263	DSB		366	3.1994	0.1555	3.3956	0.1859	FSN	213	153	2.3436	0.1188	2.6695	0.1082	GLYPH		366	19.5093	1.3023	3.2641	0.1768
264	DT		366	3.2112	0.1567	3.3761	0.1839	FST	24	342	3.4362	0.1298	7.4019	1.7110	GMC		366				
265	DTB	366		3.4946	0.1791	4.6564	0.2788	FT	176	190	2.7278	0.1476	4.4275	0.2265	GML	60	306	1.7708	0.0413	3.9044	0.7044
266	DTC		366	17.3513	1.1562	3.2644	0.1758	FTC	366		4.3191	0.2516	3.7370	0.1975	GMX	37	329	2.8848	0.1005	1.9455	0.2527
267	DTC*		366					FTP		366	3.1938	0.1551	3.3911	0.1856	GNJ		366				
268	DTR	354	12	2.4547	0.1116	2.5935	0.1138	FUCK		366	3.1625	0.1529	3.3662	0.1837	GNO	366		4.7225	0.2729	4.2857	0.2449
269	DUB	11	355					FUEL	366		3.5016	0.1844	3.0489	0.1519	GNT	366		3.1522	0.1553	5.8534	0.3679
270	DUCK		366	17.3232	1.1542	3.3798	0.1847	FUN	366		3.9501	0.2097	6.1988	0.4011	GOAT	38	328	3.4197	0.1281	7.8831	2.2944
271	DUO	3	363					FUNC	178	188	2.7393	0.1030	3.5660	0.2851	GOLOS	366		2.4932	0.1095	2.3772	0.1026
272	DUX	188	178	5.5837	0.2682	3.3355	0.2715	FUNK	251	115	3.0806	0.1290	3.0744	0.2015	GOOD	8	358	2.3361	0.0950	2.5947	0.1230
273	DVC		366	3.2371	0.1582	3.3896	0.1855	FUTC	15	351					GOON	150	216	1.7489	0.0519	1.7674	0.0610
274	DXC	131	235	2.2890	0.0727	3.9995	0.4160	FUZZ	104	262	2.7789	0.0988	6.9693	0.9211	GOT	117	249	5.0390	0.2244	4.2824	0.5065
275	DYN	366		3.1677	0.1573	3.6345	0.1986	FX	9	357					GOTX	152	214	1.6879	0.0393	5.8950	0.6373
276	EAC		366	3.2176	0.1568	3.3108	0.1794	FYN	260	106	2.8002	0.1299	2.6176	0.1226	GP	5	361				
277	EAGS	6	360					FYP	358	8	3.0369	0.1437	3.9353	0.2285	GPL	273	93	4.6758	0.2593	3.0698	0.1611
278	EB3		366					GAIA	112	254	2.9723	0.1423	2.4448	0.1095	GPU	159	207	4.8221	0.2174	2.2073	0.1599
279	EBC	39	327	2.3878	0.0936	2.2978	0.1074	GAKH	3	363					GRAM	302	64	2.6668	0.1092	3.1017	0.1822
280	EBET	302	64	2.9882	0.1435	3.0919	0.1586	GAM	363	3	2.9163	0.1420	4.7647	0.2775	GRAV	5	361				
281	EBIT		366					GAME	366		3.7403	0.2004	3.2471	0.1680	GRC	366		4.1780	0.2264	3.6234	0.2018
282	EBS		366	16.7400	1.1130	3.4110	0.1871	GAP	307	59	3.1724	0.1576	3.7387	0.2064	GRE	148	218	4.1504	0.1816	2.6072	0.1993
283	EBST	366		3.1596	0.1623	3.4596	0.1789	GAS	366		3.3203	0.1729	4.2546	0.2386	GREXIT	173	193	3.5836	0.1869	2.1772	0.0890
284	EBTC	363	3	2.3810	0.1038	2.5224	0.1107	GB	354	12	6.2138	0.3763	5.8977	0.3713	GRID		366				
285	EC	10	356					GBG	366		4.7291	0.2705	3.4462	0.1844	GRM		366	3.2284	0.1576	3.3018	0.1787
286	ECA	60	306	2.2764	0.1094	2.7252	0.1138	GBIT	212	154	2.3528	0.0957	2.7343	0.1346	GROW		366				
287	ECASH	328	38	2.9153	0.1328	2.4897	0.1185	GBRC		366					GRS	366		2.9696	0.1472	4.0881	0.2258
288	ECH	246	120	1.8556	0.0559	2.4504	0.1262	GBT	83	283	2.0937	0.0591	11.9231	2.2297	GRW	302	64	3.3438	0.1653	5.3645	0.3398
289	ECO	190	176	1.7989	0.0460	3.0354	0.2525	GBYTE	366		3.7552	0.2026	3.8337	0.2106	GRX	226	140	1.7898	0.0540	4.2266	0.2617
290	ECOB	80	286	13.8914	0.7022	3.0283	0.3766	GCC	294	72	2.2490	0.0897	2.4122	0.1077	GSM	2	364				
291	EDC	82	284	3.6665	0.1461	3.3565	0.4102	GCC*	94	272	2.6966	0.0960	2.2422	0.1690	GSX	2	364				
292	EDDIE	235	131	4.1115	0.2079	2.8865	0.1583	GCN	24	342	17.3513	1.1562	3.2646	0.1758	GSY	134	232	2.1669	0.0787	1.9936	0.0822
293	EDG	186	180	4.1821	0.1909	4.4078	0.3633	GCR	243	123	3.2829	0.1408	3.4547	0.2419	GUE		366	17.1052	1.1388	3.2823	0.1771
294	EDGE		366	17.2538	1.1493	3.3741	0.1843	GDC	307	59	1.4632	0.0336	1.4918	0.0371	GUN	296	70	2.2617	0.0935	2.2820	0.0945
295	EDO	366		4.4476	0.2501	4.5414	0.2669	GEMZ		366	17.7650	1.1855	3.3791	0.1847	GUNS	1	365	2.6387	0.1123	2.9410	0.1569
296	EDRC	207	159	5.2637	0.5330	4.3813	0.1946	GEN	82	284	4.0707	0.1656	3.7406	0.5843	GUP	366		3.2365	0.1610	3.6725	0.2032
297	EFL	366		3.0754	0.1538	3.3889	0.1761	GEO	366		2.6283	0.1242	2.7046	0.1224	GVT	366		3.3465	0.1744	8.3068	0.5372
298	EFYT	223	143	2.9529	0.1409	3.0603	0.1562	GER	350	16	3.9617	0.2089	2.2824	0.0998	GXC	3	363	3.5428	0.1710	2.5578	0.1294
299	EGAS	115	251	1.7487	0.0522	1.5758	0.0455	GGS		366	9.3076	0.5965	3.1006	0.1602	GXC*		366	3.2176	0.1568	3.3108	0.1794
300	EGC	366		3.7171	0.1976	3.6423	0.1986	GHC		366	17.1788	1.1412	3.2603	0.1760	GXS	366		3.6604	0.1967	3.0021	0.1480

Table 15 Summary-list of the cryptocurrencies considered on the market analysis along 2018 (part 2 out of 5)

	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N
301	ICON	209	157	13.3861	0.7402	3.7424	0.2957	MAD*	168	198	3.6625	0.1527	2.9963	0.2535	NTM	344	22	3.8359	0.1962	2.2869	0.1027
302	ICOS	198	168	2.3241	0.0788	2.1467	0.1251	MAID	366		4.0082	0.2101	3.5522	0.2011	NTO	291	75	1.5623	0.0387	2.0353	0.0832
303	ICX	366		3.6887	0.1951	3.8527	0.2150	MAN	225	141	2.8115	0.1332	2.6089	0.1196	NTRN	366		2.3372	0.0981	2.4366	0.1071
304	IEC	4	362					MANA	366		3.1776	0.1572	3.4786	0.1879	NTWK	196	170	3.7824	0.2057	1.9953	0.0736
305	IETH	287	79	3.1573	0.1404	3.4546	0.2153	MAPC	1	365					NUBIS	1	365				
306	IFC		366	3.2176	0.1568	3.3108	0.1794	MAR	331	35	3.0370	0.1470	2.3250	0.1004	NUKE	54	312	2.2728	0.0685	2.3581	0.2964
307	IFLT	347	19	3.3077	0.1648	3.4084	0.1847	MARS	327	39	3.6163	0.1918	3.6340	0.1963	NULS	366		5.9285	0.3594	4.0531	0.2288
308	IFT	91	275	6.0357	0.2776	4.9643	0.6517	MARV	118	248	2.7085	0.0954	4.0401	0.4532	NUM	112	254	3.5222	0.1410	4.7383	0.5512
309	ILC	143	223	2.6403	0.0941	2.6211	0.2059	MARX	107	259	3.2467	0.1252	3.6180	0.3947	NVC	366		3.3928	0.1759	3.3302	0.1732
310	ILT		366	17.4308	1.1618	3.3602	0.1832	MARYJ		366					NXC	366		6.1985	0.3694	3.3233	0.1792
311	IML	13	353	2.4757	0.0993	2.3935	0.1157	MAT	43	323	2.1156	0.0759	1.9952	0.0813	NXE	6	360				
312	IMPCH		366	17.7255	1.1827	3.3818	0.1849	MAT*	175	191	2.6979	0.0964	3.1162	0.2828	NXS	366		2.5425	0.1143	3.1485	0.1584
313	IMPS	151	215	5.0956	0.2840	2.8091	0.1439	MAX	325	41	2.5423	0.1010	2.3865	0.1202	NXT	366		4.6745	0.2716	3.6593	0.1966
314	IMS	107	259	1.6338	0.0348	5.8123	0.8253	MAY	114	252	5.6338	0.2594	10.6116	1.4020	NXTI		366	3.1815	0.1546	3.3897	0.1849
315	IMX		366	16.8557	1.1212	3.3739	0.1843	MBC		366	3.2085	0.1566	3.2635	0.1752	NXTTY		366	3.2176	0.1568	3.3108	0.1794
316	IN	71	295	5.4535	0.2419	3.2329	0.4297	MBI	198	168	1.8013	0.0580	1.6594	0.0498	NYAN	337	29	3.1074	0.1554	2.3717	0.1017
317	INC	213	153	2.7907	0.1350	4.6530	0.2650	MBIT	53	313	1.8640	0.0465	4.8395	0.8378	NZC	10	356				
318	INCNT	366		3.0977	0.1538	3.8250	0.2106	MBRS	328	38	3.1154	0.1539	2.4816	0.1114	OAX	366		2.4736	0.1078	5.9811	0.3723
319	IND	157	209	2.6943	0.0995	2.7850	0.2048	MCAP	286	80	2.6335	0.1075	2.3787	0.1187	OBITS	50	316	2.3804	0.0964	2.2634	0.0996
320	INDI	338	28	2.7290	0.1307	4.9210	0.2837	MCAR	348	18	2.5105	0.1183	4.5196	0.2470	OBS	6	360				
321	INFX	101	265	1.6954	0.0388	3.1257	0.3205	MCI	279	87	2.1321	0.0791	2.9156	0.1510	OCEAN	9	357				
322	INN	365	1	3.1270	0.1581	3.5932	0.1907	MCO	366		4.3202	0.2441	4.8155	0.2836	OCL	276	90	3.3643	0.1672	3.6259	0.2038
323	INSANE	55	311	2.0291	0.0550	2.8234	0.4559	MCRN	211	155	4.1010	0.1880	3.4975	0.2576	OCN	336	30	2.7368	0.1433	3.4202	0.1635
324	INSN	133	233	2.7365	0.0998	3.7851	0.3509	MDA	366		2.9533	0.1444	4.0243	0.2236	OCTO		366	17.3270	1.1545	3.3465	0.1821
325	INV	126	240	1.7869	0.0542	1.8191	0.0658	MDC		366	16.9092	1.1250	3.4089	0.1870	ODN	365	1	3.5030	0.1840	4.5386	0.2630
326	IOC	366		3.4213	0.1771	3.4503	0.1831	MDT	260	106	2.2885	0.0935	2.2185	0.0918	ODNT	91	275	8.7389	0.4222	3.9787	0.5438
327	ION	366		2.6489	0.1209	2.5979	0.1191	MEC	201	165	3.6796	0.1807	3.8632	0.2370	OK	366		4.9290	0.2821	6.0155	0.3824
328	IOP	366		3.7541	0.1977	5.3588	0.3324	MED	189	177	2.9489	0.1351	3.0321	0.1617	OLDSF		366	17.7345	1.1833	3.3795	0.1847
329	IOT	366		3.9811	0.2180	3.0741	0.1550	MEDI	19	347	2.1155	0.0795	1.9506	0.0731	OLYMP	124	242	5.7187	0.2671	16.1760	2.0652
330	IOU		366	3.2115	0.1564	3.3808	0.1848	MEGA		366	17.2039	1.1458	3.2641	0.1757	OMA	6	360				
331	IPC		366	17.7296	1.1830	3.3971	0.1860	MEME	366		3.4285	0.1753	3.8939	0.2194	OMC	57	309	3.7511	0.1488	4.5825	0.7313
332	IRL	354	12	3.2773	0.1697	2.7019	0.1248	MEOW		366	9.1532	0.5915	3.2120	0.1667	OMG	366		3.8290	0.2074	3.5568	0.1906
333	ISL	59	307	3.7748	0.1500	4.6637	0.7479	MER	366		3.4740	0.1795	3.5796	0.1944	OMNI	366		3.1472	0.1542	4.2855	0.2505
334	ITT	214	152	2.1173	0.0788	2.0078	0.0785	MET		366	17.3513	1.1562	3.2646	0.1758	ONION	365	1	3.8087	0.2048	3.3247	0.1742
335	ITZ		366	17.4637	1.1642	3.3660	0.1836	METAL	95	271	2.7348	0.3020	3.5826	0.1415	ONX	304	62	5.4959	0.3305	5.5451	0.3378
336	IVZ	133	233	2.0155	0.0722	2.0497	0.0810	MG		366	3.2132	0.1565	3.2921	0.1779	OPAL	61	305	4.0350	0.1641	4.2255	0.6584
337	IW	6	360					MGO	91	275	2.3272	0.0740	1.7577	0.1142	OPC	365	1	4.1967	0.2357	3.0509	0.1520
338	IWT	21	345	2.1707	0.0814	1.9359	0.0742	MHC	11	355					OPES	3	363				
339	IXC	5	361					MI		366					OPT	360	6	37.4987	2.5617	17.0807	1.2595
340	IXT	366		2.9788	0.1455	3.4358	0.1811	MIC		366					OPTION	113	253	3.2485	0.1582	9.9078	0.6956
341	J	301	65	3.3829	0.1698	3.2066	0.1697	MIL		366	3.2122	0.1564	3.2968	0.1783	ORB	364	2	3.1091	0.1563	4.9902	0.2942
342	JANE	112	254	4.2527	0.1821	4.2870	0.4795	MILO	88	278	19.9998	1.0475	5.8806	0.8024	ORLY	105	261	5.1370	0.7313	5.4736	0.2448
343	JBS		366	3.1304	0.1518	3.3482	0.1806	MIN		366	3.2186	0.1569	3.3820	0.1849	ORME	366		3.3820	0.1756	2.9566	0.1450
344	JET		366	3.2176	0.1568	3.3108	0.1794	MINE		366	17.5738	1.1749	3.3625	0.1828	ORO		366				
345	JIF	210	156	2.3400	0.0967	2.6115	0.1222	MINEX	264	102	3.0669	0.1507	2.1589	0.0869	OS76	38	328	6.3478	0.2863	7.9482	1.6852
346	JIO		366					MINT	365	1	1.4032	0.0300	4.4800	0.2559	OSC	301	65	2.8560	0.1336	2.3760	0.1046
347	JKC		366	17.4308	1.1677	3.3344	0.1801	MKR	366		2.9447	0.1438	2.5547	0.1149	OTN	366		2.2233	0.0878	3.4029	0.1832
348	JNS	4	362					MLITE	89	277	2.7938	0.0989	6.4561	0.8970	OTX	30	336	2.2861	0.0684	1.9550	0.2757
349	JNT	322	44	2.4959	0.1343	4.1292	0.2012	MLN	366		4.4620	0.2512	3.3566	0.1776	OX	42	324	1.8518	0.2066	1.7245	0.0388
350	JOBS	148	218	4.6228	0.2064	4.3327	0.4376	MLS		366					OXY	349	17	3.0072	0.1472	2.9506	0.1454
351	JOK	184	182	2.2753	0.0925	2.1809	0.0890	MM	135	231	1.8326	0.0575	3.9932	0.2396	PAC	190	176	2.0002	0.0848	2.3662	0.0907
352	JUDGE		366	17.3646	1.1572	3.3914	0.1856	MMC		366	3.2345	0.1584	3.3954	0.1854	PAK	226	140	3.1952	0.1291	2.5991	0.1822
353	JWL	107	259	8.5930	0.4149	11.9890	1.9737	MMNXT		366	17.4638	1.1642	3.3805	0.1848	PAL	164	202	1.6940	0.0481	2.1445	0.0911
354	KARMA	290	76	4.0222	0.1997	3.6059	0.2226	MMXIV		366					PARA	141	225	1.6932	0.0490	7.1844	0.4800
355	KAT	136	230	4.1619	0.1741	4.1017	0.5169	MMXVI	8	358					PART	366		3.2069	0.1659	4.2451	0.2360
356	KAYI		366	3.1992	0.1559	3.3563	0.1823	MN		366	3.1768	0.1567	3.5213	0.1917	PASC	366		3.4191	0.1803	4.9331	0.2884
357	KBC	169	197	2.2329	0.0960	2.6584	0.1170	MNC	321	45	2.7906	0.1386	3.9944	0.2123	PASL	292	74	5.9582	0.3560	3.1083	0.1608
358	KBR	363	3	2.9926	0.1453	3.2984	0.1723	MND	8	358					PAY	366		3.7121	0.1978	4.5837	0.2686
359	KC	137	229	2.2239	0.0874	2.2552	0.0963	MNE	159	207	1.9049	0.0629	1.8464	0.0671	PAYP	202	164	2.6728	0.1001	3.6188	0.2808
360	KCS	366		2.3638	0.1005	3.3713	0.1758	MNM	84	282	5.6016	0.2525	2.7135	0.2939	PBC		366				
361	KDC	222	144	2.7622	0.1282	3.4469	0.1839	MNTP	352	14	2.5311	0.1108	2.5537	0.1175	PBL	365	1	3.0256	0.1518	3.4183	0.1764
362	KED	291	75	5.2396	0.3143	3.4561	0.1811	MNX	353	13	3.2297	0.1690	3.4024	0.1734	PCM	79	287	2.0870	0.0591	8.7746	1.4693
363	KEK	336	30	2.8711	0.1399	4.4426	0.2517	MNY		366					PCOIN	364	2	2.9155	0.1432	4.8918	0.2846
364	KEN	16	350	2.0769	0.0779	2.1656	0.0881	MOAC	121	245	2.5278	0.1120	12.1634	0.8321	PCS	28	338	5.5857	0.2458	1.8986	0.2118
365	KEY	349	17	2.6698	0.1202	2.6156	0.1228	MOD	366		3.2795	0.1676	3.1213	0.1577	PDC	83	283	2.1437	0.0764	2.7819	0.1495
366	KGC	277	89	1.5428	0.0381	6.3996	0.4229	MOIN	350	16	4.2598	0.2416	4.5396	0.2609	PEC		366				
367	KICK	366		3.1183	0.1611	3.9011	0.2088	MOJO	315	51	2.2957	0.0953	2.8338	0.1363	PEN*	50	316	7.7217	0.3603	1.8887	0.2095
368	KIN	346	20	3.1352	0.1549	4.5096	0.2645	MOL		366	9.2690	0.5937	3.1017	0.1602	PEPECASH	360	6	2.1924	0.0865	2.8971	0.1430
369	KING	212	154	2.9573	0.1435	3.4567	0.1831	MONA	366		3.1482	0.1592	1.8974	0.0662	PEX	219	147	4.0141	0.2187	2.1054	0.0833
370	KLC	62	304	2.0748	0.2194	2.1139	0.0602	MONETA	198	168	1.5866	0.0418	1.7488	0.0576	PFR	321	45	2.8743	0.1393	2.4360	0.1056
371	KMD	366		3.8167	0.2060	4.4617	0.2587	MONEY	147	219	5.1204	0.2336	7.6162	0.8921	PGL	43	323	1.9153	0.0642	1.7706	0.0604
372	KNC	366		4.2595	0.2390	4.4614	0.2580	MONK	316	50	2.8037	0.1352	3.4796	0.1808	PHO	103	263	2.3017	0.0925	2.2261	0.0946
373	KOBO	113	253	3.8159	0.1564	3.1737	0.3354	MOON		366					PHR	203	163	2.4426	0.0935	2.2799	0.1131
374	KOLION	366		3.4161	0.1659	5.2531	0.3427	MOOND	77	289	4.1021	0.1695	5.3226	0.7764	PHS	219	147	2.8400	0.1364	3.4619	0.1815
375	KORE	366		3.4309	0.1832	3.4832	0.1801	MOTO	114	252	8.1361	1.2817	12.5896	0.6332	PHX	281	85	1.6253	0.0501	1.8149	0.0562
376	KR	2	364					MPRO	251	115	1.9958	0.0736	5.3930	0.3247	PIE	98	268	7.6072	0.3643	4.1216	0.5132
377	KRAK	1	365					MRP	273	93	2.3645	0.0975	1.9177	0.0704	PIGGY	343	23	4.3751	0.2488	5.7784	0.3542
378	KRB	353	13	3.5817	0.1908	3.4669	0.1824	MRS		366	17.4477	1.1630	3.3472	0.1822	PING	10	356				
379	KRC		366					MRSA		366	17.3513	1.1562	3.2646	0.1758	PINK	366		3.5440	0.1901	3.5451	0.1861
380	KRONE	5	361					MRT	9	357					PINKX	156	210	2.1692	0.0827	1.9962	0.0773
381	KSS	20	346	2.3381	0.0949	2.2419	0.0961	MRV	26	340	2.6236	0.1231	2.7649	0.1274	PIO	2	364				
382	KTK	34	332	2.6236	0.0864	5.1714	1.1569	MRY		366	17.3772	1.1580	3.3568	0.1829	PIVX	366		3.9981	0.2181	3.2467	0.1689
383	KURT	62	304	2.7942	0.0965	2.6667	0.3727	MSC		366	3.1114	0.1471	3.3483	0.1856	PIX	325	41	3.3106	0.1722	3.2422	0.1644
384	KUSH	79	287	2.4294	0.2918	3.9726	0.1607	MSD	345	21	2.2089	0.0919	3.2515	0.1621	PIZZA	21	345				
385	LA	366		3.2898	0.1794	2.4019	0.0984	MSP	364	2	3.5116	0.1789	4.0978	0.2383	PKB	86	280	4.4850	0.1918	3.3453	0.3909
386	LAB		366	18.1011	1.2123	3.4096	0.1865	MST	90	276	2.8378	0.0991	2.9870	0.4236	PLANET	77	289	3.0864	0.1140	7.2694	1.1260
387	LANA	129	237	1.9096	0.0643	1.8265	0.0642	MTC	224	142	2.1634	0.0980	3.4167	0.1611	PLAY	322	44	2.2779	0.1065	2.6344	0.1097
388	LAT	182	184	2.1501	0.0862	2.3106	0.0956	MTH	366		3.0081	0.1493	3.4307	0.1787	PLBT	276	90	3.5494	0.1885	2.9137	0.1415
389	LAZ	87	279	7.8181	0.3692	4.4010	0.6802	MTL	366		5.6395	0.3297	3.7809	0.2146	PLC	363	3	2.9110	0.1386	2.9912	0.1501
390	LBC	366		3.1650	0.1523	5.5178	0.3528	MTR		366	17.4308	1.1677	3.3344	0.1801	PLNC	88	278	2.9857	0.1082	3.2005	0.4086
391	LBTC	291	75	1.6358	0.0436	1.6694	0.0541	MUDRA		366					PLR	366		2.4683	0.1110	3.6369	0.1908
392	LC	128	238	5.1946	0.2345	4.2536	0.4797	MUE	366		2.3083	0.0972	3.1172	0.1557	PLU	338	28	7.1587	0.4565	3.9769	0.2195
393	LCASH	6	360	2.1877	0.1159	3.6552	0.1644	MUSIC	366		3.7084	0.2065	2.4381	0.1032	PLX	146	220	2.2053	0.0863	3.2812	0.1744
394	LCP	365	1	3.8796	0.2089	4.1078	0.2343	MUU	218	148	5.1778	0.2524	3.3774	0.2479	PNC	4	362				
395	LDC	366		2.3166	0.0940	2.8433	0.1414	MWC		366	17.4308	1.1677	3.3344	0.1801	PND	295	71	3.1493	0.1390	4.5423	0.3143
396	LDM	177	189	1.5931	0.0344	3.8133	0.3387	MXT	119	247	1.7787	0.0553	1.7600	0.0586	PNK	126	240	2.0729	0.0762	2.3071	0.1008
397	LDOGE	339	27	3.0209	0.1401	4.0966	0.2464	MYB	366		2.3253	0.0954	2.4261	0.1084	POE	366		3.2774	0.1635	4.4780	0.2652
398	LEA	151	215	3.5823	0.1464	4.4165	0.4607	MYC		366					POINTS		366	17.7727	1.1860	3.3532	0.1826
399	LEAF	243	123	3.3160	0.1450	3.7295	0.2591	MYST	282	84	2.4146	0.0983	2.3243	0.1050	POLL	366		3.4472	0.1850	3.7477	0.1988
400	LEMON		366					MZC	213	153	3.2323	0.1571	8.3615	0.5748	POLY	273	93	2.6253	0.1415	4.4816	0.2276
401	LEND	366		7.8183	0.4973	2.9079	0.1430	N7	4	362					NTM	344	22	3.8359	0.1962	2.2869	0.1027
402	LENIN	104	262	4.4966	0.1928	4.2367	0.5321	NAMO	19	347					NTO	291	75	1.5623	0.0387	2.0353	0.0832
403	LEO	203	163	3.4425	0.1801	3.3404	0.1735	NAN		366	17.7345	1.1833	3.3795	0.1847	NTRN	366		2.3372	0.0981	2.4366	0.1071
404	LEPEN	183	183	3.6346	0.1561	4.8853	0.4317	NANAS	43	323	8.5107	0.4009	3.0290	0.5239	NTWK	196	170	3.7824	0.2057	1.9953	0.0736
405	LFC		366					NAS	358	8	2.5834	0.1405	5.4324	0.2867	NUBIS	1	365				
406	LGBTQ	94	272	3.1524	0.1172	2.7120	0.3179	NAS2		366	3.2265	0.1578	3.2630	0.1751	NUKE	54	312	2.2728	0.0685	2.3581	0.2964
407	LGD	172	194	3.6635	0.1874	3.7838	0.2174	NAUT		366	3.1574	0.1526	3.3564	0.1829	NULS	366		5.9285	0.3594	4.0531	0.2288
408	LIFE	366		1.4486	0.0309	1.3423	0.0275	NAV	366		5.1223	0.3047	6.3179	0.3931	NUM	112	254	3.5222	0.1410	4.7383	0.5512
409	LIMX	5	361					NBIT	65	301	3.3147	0.1248	3.5021	0.5334	NVC	366		3.3928	0.1759	3.3302	0.1732
410	LINDA	366		2.8931	0.1435	3.6794	0.1934	NBL		366	17.6852	1.1798	3.3821	0.1849	NXC	366		6.1985	0.3694	3.3233	0.1792
411	LINK	366		3.9279	0.2182	3.8696	0.2104	NBT	2	364					NXE	6	360				
412	LINX	365	1	4.0666	0.2318	3.4456	0.1770	NDC	362	4	2.1523	0.0864	3.5315	0.1846	NXS	366		2.5425	0.1143	3.1485	0.1584
413	LIR	11	355					NDOGE	150	216	2.3531	0.0945	2.4533	0.1145	NXT	366		4.6745	0.2716	3.6593	0.1966
414	LIT	255	111	2.9168	0.1383	2.0383	0.0787	NEBL	366		2.7856	0.1361	5.1039	0.2946	NXTI		366	3.1815	0.1546	3.3897	0.1849
415	LIV	158	208	2.4794	0.0851	4.0385	0.3798	NEBU	133	233	1.8246	0.0600	2.0028	0.0754	NXTTY		366	3.2176	0.1568	3.3108	0.1794
416	LK7		366	17.7345	1.1833	3.3795	0.1847	NEC		366	3.2297	0.1577	3.3849	0.1851	NYAN	337	29	3.1074	0.1554	2.3717	0.1017
417	LKK	366		3.3512	0.1724	3.2284	0.1661	NEF	111	255	2.9069	0.1068	7.1919	0.9032	NZC	10	356				
418	LKY		366	17.7296	1.1830	3.3971	0.1860	NEO	366		3.1078	0.1558	3.2856	0.1690	OAX	366		2.4736	0.1078	5.9811	0.3723
419	LMC	286	80	3.5482	0.1648	2.4528	0.1289	NEOG	107	259	1.7826	0.0559	1.7166	0.0550	OBITS	50	316	2.3804	0.0964	2.2634	0.0996
420	LNK	62	304	2.0081	0.0691	1.7883	0.0637	NEOS	366		4.2061	0.2296	4.1807	0.2432	OBS	6	360				
421	LOC	129	237	2.9699	0.1110	2.6043	0.2247	NET	302	64	2.4679	0.1041	2.6550	0.1281	OCEAN	9	357				
422	LOCI	346	20	2.9010	0.1421	2.4706	0.1075	NETC	123	243	1.9837	0.0697	2.9779	0.1531	OCL	276	90	3.3643	0.1672	3.6259	0.2038
423	LOG	274	92	2.4103	0.1031	2.9307	0.1443	NETKO	78	288	1.3324	0.0179	4.9065	0.8525	OCN	336	30	2.7368	0.1433	3.4202	0.1635
424	LOOK	133	233	3.5089	0.1409	3.8858	0.4123	NEU	361	5	2.2596	0.0990	3.2619	0.1584	OCTO		366	17.3270	1.1545	3.3465	0.1821
425	LQD		366	2.9826	0.1385	3.2533	0.1776	NEVA	7	359					ODN	365	1	3.5030	0.1840	4.5386	0.2630
426	LRC	366		3.0225	0.1479	4.4333	0.2566	NEWB	19	347					ODNT	91	275	8.7389	0.4222	3.9787	0.5438
427	LSD	10	356					NGC	366		2.6258	0.1164	3.6980	0.2063	OK	366		4.9290	0.2821	6.0155	0.3824
428	LSK	366		3.7144	0.1985	3.1161	0.1582	NIC	57	309	3.6033	0.1416	4.0576	0.5778	OLDSF		366	17.7345	1.1833	3.3795	0.1847
429	LTB	325	41	2.3005	0.0961	4.3704	0.2491	NICE	60	306	5.9461	0.2667	2.3850	0.2953	OLYMP	124	242	5.7187	0.2671	16.1760	2.0652
430	LTBC		366	17.3270	1.1545	3.3465	0.1821	NIMFA	75	291	1.9538	0.0642	1.7136	0.0593	OMA	6	360				
431	LTC	366		3.6684	0.1967	6.7317	0.4249	NKA	186	180	2.9803	0.1147	4.0734	0.3727	OMC	57	309	3.7511	0.1488	4.5825	0.7313
432	LTCD		366	17.4880	1.1659	3.2646	0.1758	NKC	282	84	2.4801	0.1109	2.4903	0.1087	OMG	366		3.8290	0.2074	3.5568	0.1906
433	LTCR	165	201	2.4426	0.0827	6.8462	0.7425	NKT	78	288	4.2407	0.1771	3.2218	0.3990	OMNI	366		3.1472	0.1542	4.2855	0.2505
434	LTCU	195	171	3.5531	0.1512	5.1437	0.4604	NLC		366					ONION	365	1	3.8087	0.2048	3.3247	0.1742
435	LTCX		366	16.8557	1.1212	3.3739	0.1843	NLC2	366		2.2986	0.0971	3.4844	0.1817	ONX	304	62	5.4959	0.3305	5.5451	0.3378
436	LTD	344	22	3.6743	0.1966	3.7099	0.2014	NLG	366		6.5585	0.4087	3.8301	0.2104	OPAL	61	305	4.0350	0.1641	4.2255	0.6584
437	LTE		366	9.4502	0.6098	3.1840	0.1656	NMB		366	17.3513	1.1562	3.2644	0.1758	OPC	365	1	4.1967	0.2357	3.0509	0.1520
438	LTG	100	266	1.6457	0.0437	1.5415	0.0445	NMC	366		4.0573	0.2230	3.4827	0.1861	OPES	3	363				
439	LTH	9	357					NMR	366		4.2004	0.2412	5.1707	0.3026	OPT	360	6	37.4987	2.5617	17.0807	1.2595
440	LTS	321	45	2.0891	0.0792	2.3695	0.1029	NMS	363	3	3.1051	0.1539	3.7281	0.2039	OPTION	113	253	3.2485	0.1582	9.9078	0.6956
441	LUCKY	73	293	3.1881	0.1190	3.3525	0.4446	NOBL		366					ORB	364	2	3.1091	0.1563	4.9902	0.2942
442	LUN	366		3.1187	0.1549	3.3336	0.1744	NODE		366	3.2176	0.1568	3.3108	0.1794	ORLY	105	261	5.1370	0.7313	5.4736	0.2448
443	LUX	365	1	3.2681	0.1719	3.8149	0.2031	NOO		366					ORME	366		3.3820	0.1756	2.9566	0.1450
444	LUX*	153	213	1.6672	0.0467	1.7912	0.0622	NPC	1	365					ORO		366				
445	LVG	168	198	1.8881	0.0628	1.9718	0.0754	NRB		366	17.3513	1.1562	3.2644	0.1758	OS76	38	328	6.3478	0.2863	7.9482	1.6852
446	LXC		366	17.2667	1.1502	3.2741	0.1765	NRC	137	229	2.7726	0.1263	2.1964	0.0920	OSC	301	65	2.8560	0.1336	2.3760	0.1046
447	LYB		366					NRS		366	17.7909	1.1873	3.3758	0.1844	OTN	366		2.2233	0.0878	3.4029	0.1832
448	LYC	2	364	2.7458	0.1270	2.3270	0.0997	NSR		366					OTX	30	336	2.2861	0.0684	1.9550	0.2757
449	M1	3	363					NTC		366					OX	42	324	1.8518	0.2066	1.7245	0.0388
450	MAC	290	76	3.4431	0.1670	2.6185	0.1313	NTCC		366					OXY	349	17	3.0072	0.1472	2.9506	0.1454

Table 16 Summary-list of the cryptocurrencies considered on the market analysis along 2018 (part 3 out of 5)

	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N
451	POP		366					SGR	159	207	1.8905	0.0619	1.9225	0.0732	TKR	291	75	3.4968	0.1774	2.4033	0.1083
452	POS		366	17.3766	1.1580	3.3866	0.1852	SH	79	287	2.7528	0.0956	2.0304	0.1881	TKS	366		3.5705	0.1932	4.4858	0.2536
453	POST	346	20	3.0433	0.1486	3.8890	0.2171	SHA	327	39	3.6897	0.1897	3.9712	0.2313	TMC		366	18.8985	1.2562	3.4334	0.1906
454	POT	366		4.2161	0.2371	3.3656	0.1753	SHADE		366	3.2176	0.1568	3.4052	0.1867	TME		366	17.7345	1.1833	3.3795	0.1847
455	POWR	366		3.1580	0.1557	3.3608	0.1790	SHIFT	366		4.0656	0.2236	4.1247	0.2342	TNT	366		2.8784	0.1377	3.7680	0.2063
456	PPC	366		2.5232	0.1074	3.4746	0.1926	SHLD		366	17.8368	1.1905	3.3762	0.1844	TOA	15	351	3.7650	0.1819	2.4089	0.1213
457	PPP	330	36	2.7786	0.1297	3.0132	0.1509	SHND	193	173	2.0126	0.0712	1.8861	0.0692	TODAY	231	135	1.6853	0.0475	5.3793	0.3484
458	PPT	366		3.9029	0.2152	3.5398	0.1872	SHORTY	225	141	2.8975	0.1362	1.9184	0.0700	TOK	360	6	3.8576	0.2160	3.8560	0.2067
459	PPY	330	36	5.8895	0.3644	5.5364	0.3326	SHREK	172	194	2.9472	0.1141	4.1955	0.3690	TOKC	297	69	2.1171	0.1060	3.0003	0.1253
460	PRC	73	293	2.3396	0.0732	1.8659	0.1555	SIB	366		3.4982	0.1888	2.2693	0.0918	TOM	1	365	3.0855	0.1378	3.1071	0.1800
461	PRE	106	260	2.6783	0.0932	2.6927	0.2612	SIC	78	288	4.6795	0.1995	4.8643	0.7579	TOR		366				
462	PRES	346	20	2.4359	0.1036	2.5023	0.1139	SIFT	96	270	2.0412	0.0748	1.9989	0.0762	TOT	110	256	2.7141	0.0945	2.8209	0.2993
463	PRFT	57	309	1.8997	0.0641	1.8058	0.0620	SIGT	138	228	2.5115	0.0849	8.6747	1.0964	TPG	178	188	1.6255	0.0433	1.7168	0.0572
464	PRG	361	5	2.9513	0.1442	2.1472	0.0848	SILK		366	3.2004	0.1556	3.3840	0.1850	TRA	1	365				
465	PRIME		366					SISA	173	193	1.8572	0.0611	1.8954	0.0689	TRC	33	333	1.8913	0.0476	2.1610	0.2903
466	PRIX	106	260	2.1791	0.0658	5.8157	0.7179	SJCX	101	265	1.9248	0.0628	1.7922	0.0649	TRCT	345	21	3.4291	0.1791	3.7059	0.2006
467	PRL	302	64	3.2014	0.1606	3.2028	0.1651	SKB	301	65	2.1995	0.0852	4.7907	0.2925	TREE	3	363				
468	PRM	154	212	2.9921	0.1368	2.1317	0.0912	SKC	364	2	2.7114	0.1276	3.6115	0.1915	TRI	332	34	2.9642	0.1425	7.9789	0.5261
469	PRO	366		3.9559	0.2228	4.2803	0.2380	SKIN	361	5	4.0005	0.2165	3.0779	0.1575	TRIA	142	224	1.8078	0.0555	1.7918	0.0638
470	PROC	7	359					SKR	349	17	4.1334	0.2291	8.6878	0.5746	TRICK	63	303	2.6097	0.0868	2.1167	0.2381
471	PRT		366	3.2371	0.1582	3.3896	0.1855	SKULL	103	263	4.4966	0.1925	5.0374	0.6729	TRIG	286	80	3.8216	0.2010	3.4757	0.1904
472	PRX	79	287	2.6924	0.0930	2.4926	0.2523	SKY	365	1	4.3058	0.2398	3.6130	0.1970	TRK	353	13	3.0949	0.1536	3.1852	0.1629
473	PSB	64	302	3.8610	0.1549	3.1777	0.4355	SLG	245	121	2.2594	0.0909	3.8846	0.2187	TROLL	354	12	3.2586	0.1626	3.2028	0.1675
474	PSEUD		366	17.3513	1.1562	3.2644	0.1758	SLM		366					TRST	186	180	2.6304	0.0976	3.4093	0.2583
475	PSI	135	231	1.8477	0.0607	1.9181	0.0702	SLR	366		3.3519	0.1778	3.2972	0.1662	TRUMP	221	145	2.1116	0.0817	1.9300	0.0691
476	PST	366		4.0241	0.2286	3.6730	0.1934	SLS	366		3.4925	0.1884	3.5756	0.1864	TRUST	300	66	2.4083	0.1019	2.3363	0.1010
477	PSY	6	360					SLT	16	350	1.9346	0.0766	2.3547	0.0920	TRV	5	361	3.3070	0.1603	2.8285	0.1450
478	PTA	27	339	2.7136	0.0909	4.0966	0.9337	SMAC		366	17.3781	1.1581	3.2932	0.1780	TRX	366		3.0589	0.1552	2.4484	0.1051
479	PTC	365	1	3.7516	0.2001	3.6879	0.2020	SMART	366		2.5142	0.1138	2.5001	0.1091	TSC	10	356	3.0125	0.1305	2.7258	0.1525
480	PTOY	339	27	2.9787	0.1428	2.9651	0.1490	SMART*	10	356	2.5852	0.1253	2.9605	0.1366	TSE	113	253	4.0188	0.1685	4.6199	0.5396
481	PULSE	68	298	4.8396	0.2079	3.5741	0.5148	SMC	108	258	4.6379	0.2021	3.5930	0.4001	TTC	201	165	6.0868	0.3035	6.1722	0.5610
482	PUPA	232	134	3.4105	0.1709	1.9508	0.0736	SMF	12	354					TUBE	204	162	4.3836	0.2474	5.0529	0.3029
483	PURA	349	17	4.1100	0.2312	3.7961	0.2056	SMLY	38	328	4.1853	0.2275	3.4143	0.1852	TUR	139	227	1.7302	0.0533	1.8259	0.0619
484	PUT	366		2.8004	0.1317	2.9567	0.1462	SMSR	65	301	2.8207	0.0976	3.2093	0.5207	TWIST	29	337	7.5751	0.3500	5.2296	1.1731
485	PX	99	267	3.2760	0.1247	5.6017	0.8010	SNC	366		3.1147	0.1551	3.1518	0.1604	TWLV		366				
486	PXC	365	1	2.1578	0.0856	2.6040	0.1186	SND	214	152	1.5850	0.0421	2.8529	0.1409	TX	366		3.3779	0.1763	5.3671	0.3219
487	PXI	90	276	3.8298	0.1546	3.0581	0.3696	SNGLS	366		2.2981	0.0952	3.2647	0.1688	TZC	364	2	2.0510	0.0753	3.3764	0.1817
488	PXL	155	211	2.1188	0.0797	2.6972	0.1306	SNIP	93	273	1.8286	0.0625	1.8086	0.0587	U	87	279	2.9313	0.3586	4.2009	0.1744
489	PYC		366	3.2136	0.1565	3.3814	0.1848	SNM	366		5.6383	0.3330	3.9968	0.2285	UBC		366	3.1986	0.1555	3.3561	0.1829
490	PYN	340	26	3.2981	0.1637	3.0013	0.1539	SNOV	366		3.1889	0.1645	3.8824	0.2097	UBIQ	237	129	3.1169	0.1504	2.2699	0.0980
491	Q2C	301	65	3.0453	0.1472	2.2713	0.0967	SNRG	83	283	4.6132	0.1983	2.1485	0.1970	UBQ	366		4.0707	0.2182	3.5756	0.1987
492	QASH	366		3.2940	0.1715	2.0532	0.0770	SNT	366		3.1962	0.1610	3.6679	0.1989	UBTC	363	3	2.5873	0.1164	3.0743	0.1546
493	QAU	123	243	3.3899	0.1362	3.9197	0.3834	SOAR	355	11	3.2065	0.1592	2.3955	0.1058	UET	319	47	2.4095	0.1059	3.6883	0.1955
494	QBC	318	48	3.2942	0.1724	3.5449	0.1851	SOCC	321	45	4.7676	0.2763	3.9327	0.2186	UETL	6	360	3.4979	0.1841	3.9123	0.2159
495	QBK		366	3.2192	0.1565	3.3447	0.1825	SOIL	326	40	4.7351	0.2823	3.2416	0.1622	UFO		366	17.3513	1.1562	3.2646	0.1758
496	QBT	315	51	3.0637	0.1513	2.5412	0.1149	SOJ	66	300	1.8238	0.0660	2.1472	0.0792	UIS	72	294	5.5135	0.2416	2.3255	0.3215
497	QCN	174	192	1.7655	0.0529	1.7199	0.0575	SOLE		366	17.3848	1.1615	3.3329	0.1805	UKG	366		2.5957	0.1180	3.6466	0.1956
498	QORA		366					SONG	10	356					UMC	4	362				
499	QRK	322	44	3.3544	0.1731	3.6934	0.2002	SOON	303	63	2.2370	0.0905	3.9716	0.2221	UMO	324	42	3.6650	0.1992	7.1473	0.4495
500	QRL	366		2.2417	0.0908	3.4120	0.1803	SOUL	232	134	4.9502	0.2408	2.8682	0.1897	UNAT		366	17.7171	1.1821	3.3645	0.1835
501	QSLV		366	17.1052	1.1388	3.2823	0.1771	SP	104	262	3.4116	0.1334	2.1440	0.1832	UNB		366				
502	QSP	366		3.1295	0.1570	4.4477	0.2556	SPA		366	17.3513	1.1562	3.2644	0.1758	UNC		366				
503	QTL	315	51	2.8181	0.1348	2.4025	0.1034	SPACE	130	236	5.3057	0.2426	7.8936	0.9653	UNF	153	213	3.2794	0.1645	2.8237	0.1383
504	QTUM	366		3.4711	0.1802	4.3389	0.2503	SPANK	340	26	3.0822	0.1507	2.6006	0.1210	UNI	231	135	5.5992	0.2799	6.0129	0.5116
505	QTZ	32	334	10.7377	0.5168	11.8621	3.2750	SPC	2	364					UNIFY	129	237	3.5597	0.1459	6.4831	0.7200
506	QWARK	366		2.6509	0.1207	3.4323	0.1818	SPEC	7	359					UNIQ		366	17.6705	1.1817	3.3036	0.1783
507	R	366		2.9954	0.1535	3.9822	0.2125	SPF	366		3.2752	0.1705	4.1288	0.2282	UNIT	331	35	2.3554	0.1005	2.3983	0.1031
508	RAC		366	3.5895	0.1864	3.6659	0.2027	SPHR	366		3.0257	0.1466	3.1621	0.1634	UNITS	98	268	3.2658	0.1261	1.5904	0.0900
509	RADI	116	250	3.4708	0.1366	3.8483	0.4561	SPKTR	70	296	4.1932	0.1719	4.0286	0.6609	UNITY		366	3.2588	0.1597	3.3478	0.1822
510	RADS	366		3.2572	0.1673	3.4403	0.1799	SPM	132	234	1.8208	0.0591	1.8898	0.0677	UNO	36	330	1.7410	0.0397	1.6324	0.1490
511	RAIN		366					SPORT	174	192	1.7275	0.0522	4.2797	0.2501	UNRC	255	111	2.8173	0.1147	3.2224	0.2072
512	RATIO	65	301	9.0470	0.4326	3.6127	0.5842	SPOTS		366					UQC	346	20	1.9458	0.0699	2.2476	0.0922
513	RBIES	288	78	1.9491	0.0690	2.8799	0.1413	SPR	116	250	2.8793	0.1051	2.6707	0.2463	UR	199	167	3.2021	0.1520	2.9761	0.1582
514	RBIT	127	239	1.3472	0.0193	45.5471	6.7157	SPRTS		366	17.3513	1.1562	3.2646	0.1758	URO	2	364				
515	RBR		366	3.2086	0.1562	3.3807	0.1848	SPT	82	284	11.9043	0.5958	6.1092	0.9176	USC	166	200	2.6120	0.0914	2.8121	0.2443
516	RBT	166	200	1.7603	0.0556	3.4465	0.1829	SPX	173	193	1.9635	0.0688	2.2565	0.0964	USDE	236	130	3.1727	0.1597	3.3956	0.1781
517	RBX	87	279	1.9074	0.0605	1.7425	0.0625	SQL	72	294	4.2828	0.1755	6.1945	1.2986	USDT	366		1.6039	0.0396	2.8479	0.1596
518	RBY	115	251	6.9472	0.3314	2.2607	0.1901	SRC	354	12	2.3575	0.1015	4.0325	0.2218	UTC	350	16	3.5919	0.1871	4.3797	0.2562
519	RC	342	24	2.5183	0.1186	2.8692	0.1315	SRN	365	1	3.4072	0.1746	4.9464	0.2975	UTH		366	17.7296	1.1830	3.3971	0.1860
520	RCN	366		4.5112	0.2534	5.8775	0.3698	SSC	361	5	2.5907	0.1182	2.6308	0.1199	UTIL		366	17.4672	1.1644	3.2691	0.1761
521	RCN*	245	121	4.4475	0.2155	6.5023	0.5246	SSD		366	3.2330	0.1587	3.3681	0.1827	UTT	336	30	4.3287	0.2509	3.5559	0.1854
522	RCX	111	255	3.4238	0.1347	4.2241	0.4975	SSTC	114	252	1.4765	0.0261	5.7845	0.8329	VAL	288	78	3.4765	0.1605	3.1670	0.1915
523	RDD	366		2.4361	0.1064	4.8815	0.2862	SSV		366	17.4308	1.1677	3.3344	0.1801	VAPOR	157	209	1.9669	0.0682	2.1000	0.0856
524	RDN*	366		4.7345	0.2709	3.9036	0.2189	STA	313	53	5.3439	0.3211	5.3952	0.3249	VDO		366	17.7464	1.1841	3.2667	0.1759
525	REBL	334	32	2.9114	0.1462	2.4020	0.1004	STA*	103	263	2.9830	0.1095	7.4775	1.0508	VEC2	212	154	2.9048	0.1302	3.0345	0.1650
526	REC	241	125	5.5454	0.3289	5.5064	0.3407	STALIN	224	142	2.9187	0.1133	5.0152	0.4517	VEG	60	306	5.0116	0.2154	5.5666	1.0477
527	REE	181	185	1.7724	0.1061	2.0192	0.0576	STAR	355	11	2.1453	0.0833	2.1893	0.0894	VERSA		366				
528	REP	366		4.4319	0.2445	3.2486	0.1730	STAR*	147	219	3.9524	0.1671	4.0346	0.4130	VET	217	149	2.8750	0.1131	2.7689	0.1854
529	REQ	366		3.4804	0.1834	3.5786	0.1906	START	164	202	5.4140	0.2544	5.8260	0.5986	VIA	366		5.1529	0.3021	3.7783	0.2088
530	REV	10	356					STAX	19	347	2.3395	0.0996	2.9737	0.1451	VIB	366		5.5078	0.3296	4.3081	0.2473
531	REX	169	197	1.7456	0.0533	2.0740	0.0824	STC	320	46	3.1726	0.1602	3.2273	0.1651	VIBE	366		2.4845	0.1132	2.8465	0.1326
532	RGC	43	323	1.5213	0.0278	2.3533	0.3617	STCN		366	16.4616	1.1044	3.3324	0.1789	VIDZ	155	211	2.4635	0.0830	5.9196	0.6634
533	RHOC	361	5	3.4248	0.1860	5.0219	0.2873	STEEM	366		3.1982	0.1676	6.4599	0.3920	VIOR		366	3.2175	0.1572	3.3631	0.1829
534	RIC	215	151	2.6094	0.1059	2.1747	0.1011	STEPS	73	293	14.1869	0.7226	3.0766	0.3615	VIP	98	268	2.5479	0.0859	4.0788	0.4808
535	RICE	152	214	1.9391	0.0672	2.1372	0.0870	STHR	93	273	2.1633	0.0814	2.2363	0.0971	VIRAL		366				
536	RIDE	187	179	1.5760	0.0407	1.7122	0.0553	STN	358	8	2.9793	0.1459	4.8452	0.2850	VISIO	102	264	7.2445	0.3491	3.2112	0.3260
537	RING	174	192	2.9477	0.1115	6.7229	0.7327	STO	283	83	1.6659	0.0465	1.6804	0.0536	VIVO	365	1	3.7493	0.2072	2.5126	0.1097
538	RIPO		366	17.3513	1.1562	3.2644	0.1758	STORJ	366		8.2527	0.5276	3.6746	0.2010	VLT	281	85	1.9362	0.0613	3.6402	0.2289
539	RIPT	61	305	2.4597	0.0822	1.3032	0.0425	STORM	366		1.9741	0.0734	2.3060	0.0947	VLTC		366				
540	RISE	325	41	1.8520	0.0602	2.2052	0.0935	STP	89	277	1.6993	0.0571	1.7616	0.0518	VMC		366	3.2371	0.1582	3.3896	0.1855
541	RIYA	11	355					STR*		366	17.7296	1.1830	3.3971	0.1860	VOISE	222	144	2.9994	0.1478	3.2920	0.1694
542	RKC	4	362					STRAT	366		3.5381	0.1813	5.7805	0.3667	VOL	158	208	1.8250	0.0603	2.1511	0.0860
543	RLC	366		3.1713	0.1596	3.4965	0.1856	STS	64	302	5.8853	0.2646	1.9737	0.1947	VOLT	177	189	1.7675	0.0555	2.7422	0.1317
544	RNC	39	327	2.2109	0.0826	2.0733	0.0873	STU	360	6	3.4621	0.1825	3.4715	0.1822	VOOT		366	3.2203	0.1570	3.3603	0.1832
545	RNS	342	24	4.3542	0.2384	4.7017	0.2856	STV	92	274	3.7511	0.1501	3.5025	0.4569	VOYA	148	218	1.8925	0.0626	3.0307	0.1591
546	ROC	25	341	2.3042	0.0983	2.4815	0.1075	STX	366		2.8764	0.1369	4.2351	0.2425	VPRC	229	137	3.3252	0.1426	2.9454	0.1945
547	ROOT		366	3.1797	0.1541	3.4056	0.1867	SUB	366		4.9334	0.2869	3.8210	0.2114	VRC	366		3.3530	0.1725	4.2732	0.2440
548	ROOTS		366	9.2677	0.5936	3.1106	0.1609	SUB*	158	208	4.4032	0.1949	5.1419	0.5303	VRM	366		3.1673	0.1576	3.4554	0.1846
549	ROS	53	313	1.8781	0.0474	1.7763	0.1619	SUMO	316	50	2.9856	0.1429	3.5015	0.1902	VRP*	107	259	4.9176	0.2166	5.0749	0.6525
550	ROUND		366	17.3161	1.1566	3.3275	0.1801	SUP		366	16.2362	1.0774	3.3831	0.1850	VRS	352	14	2.6220	0.1445	3.0918	0.1350
551	ROYAL	244	122	3.2749	0.1691	4.4100	0.2507	SUPER	7	359					VSL	177	189	3.9289	0.2031	1.9332	0.0742
552	RPC	83	283	1.9154	0.0498	1.9391	0.1775	SUR	366		3.0606	0.1549	4.7726	0.2744	VSX	1	365				
553	RRT	365	1	2.8890	0.1408	3.6190	0.1920	SWARM		366	17.7296	1.1830	3.3975	0.1861	VTA		366				
554	RSC	3	363					SWEET	130	236	2.9501	0.1097	3.8582	0.4042	VTC	366		4.0141	0.2192	2.2099	0.0909
555	RT2		366	3.2287	0.1576	3.3693	0.1839	SWFTC	366		2.9102	0.1404	2.4382	0.1069	VTL	171	195	5.1107	0.2422	6.3866	0.6099
556	RUBIT	83	283	2.0718	0.0729	1.8331	0.0680	SWIFT	132	234	2.4314	0.0992	4.1560	0.2511	VTN	77	289	2.6356	0.0887	2.2328	0.2418
557	RUP	321	45	2.8067	0.1304	2.9796	0.1501	SWING	89	277	2.7010	0.0936	2.7398	0.2900	VTR	202	164	2.6837	0.1154	3.5880	0.2092
558	RUPX	350	16	2.2963	0.1022	2.2966	0.0906	SWT	366		3.3500	0.1756	3.9916	0.2188	VTX	113	253	3.8287	0.1581	2.8746	0.2764
559	RUST	140	226	2.0530	0.0739	2.1720	0.0918	SXC	287	79	2.9599	0.1382	2.7829	0.1388	VTY	129	237	4.8875	0.2190	5.4918	0.6290
560	RVT	363	3	3.3477	0.1690	3.9782	0.2264	SXDT	333	33	4.5716	0.2655	3.0579	0.1513	VUC	47	319	1.4891	0.0261	2.3375	0.3575
561	RYC		366	17.3772	1.1580	3.3568	0.1829	SXUT	342	24	2.4612	0.1044	3.2138	0.1698	WABI	366		3.9091	0.2193	4.8654	0.2804
562	RYCN		366					SYNC	27	339	2.0935	0.0783	2.1068	0.0846	WAND	212	154	2.4660	0.1047	2.4619	0.1121
563	RYZ	243	123	3.5591	0.1770	2.1618	0.0927	SYNX	366		3.7012	0.1981	4.3533	0.2499	WARP	4	362				
564	RZR		366	3.2163	0.1567	3.3850	0.1851	SYS	366		4.2023	0.2342	3.8854	0.2157	WASH	137	229	3.6024	0.1473	2.3822	0.1881
565	S8C		366					TAAS	362	4	3.1838	0.1606	3.3672	0.1760	WAVES	366		3.0863	0.1534	2.2903	0.0959
566	SAFEX	308	58	4.3361	0.2466	4.0747	0.2273	TAB	156	210	2.7831	0.1290	2.9658	0.1486	WAY	132	234	1.9937	0.0710	2.2300	0.0943
567	SAGA	365	1	3.5157	0.1830	3.5443	0.1912	TAG	322	44	2.1024	0.0817	2.4184	0.1046	WBB	133	233	6.9090	0.3298	4.0503	0.4547
568	SALT	366		4.2646	0.2407	3.2466	0.1665	TAJ	76	290	2.5219	0.0831	2.7208	0.3091	WBTC*		366	17.3356	1.1551	3.3814	0.1848
569	SAN	366		3.0941	0.1531	2.5449	0.1155	TAK	92	274	2.9933	0.1104	3.6446	0.4181	WC	290	76	2.3037	0.0953	4.1438	0.2350
570	SAND	340	26	3.0825	0.1491	3.5890	0.1980	TAM	140	226	1.8801	0.0635	1.9677	0.0734	WCT	332	34	2.9601	0.1415	3.5078	0.1901
571	SANDG	140	226	2.6459	0.0957	4.9179	0.4683	TAP	221	145	2.5427	0.0914	3.4949	0.2772	WDC	332	34	3.4617	0.1872	2.3580	0.0978
572	SAR*		366	17.2922	1.1520	3.3740	0.1843	TBCX	137	229	2.2367	0.0702	3.2114	0.2955	WEALTH	130	236	3.2369	0.1586	3.2761	0.1761
573	SAT2	10	356	2.5924	0.1287	3.4949	0.1709	TBT	289	77	3.0082	0.1336	2.4826	0.1253	WEX	366					
574	SBTC		366	1.9959	0.0742	2.0064	0.0738	TCOIN	16	350					WGC		366				
575	SC		366	3.0609	0.1484	3.8718	0.2183	TCR	133	233	1.8144	0.0570	1.8941	0.0702	WGO	297	69	4.0239	0.2188	3.8109	0.2125
576	SCASH	164	202	3.0631	0.1179	3.6736	0.3452	TCX	221	145	6.0540	0.3081	12.4467	1.1622	WGR	236	130	1.9099	0.0673	2.9606	0.1449
577	SCL	12	354					TDFB	2	364					WHO	151	215	2.2788	0.0736	2.6278	0.2035
578	SCN		366					TEAM	112	254	4.4822	0.1929	3.5604	0.4048	WIC	126	240	1.8851	0.0497	2.9464	0.2781
579	SCOOBY	195	171	1.6743	0.0510	1.7045	0.0510	TEC	127	239	1.9764	0.0690	2.2462	0.0967	WILD	360	6	3.7805	0.1996	4.2250	0.2459
580	SCORE		366	17.3772	1.1580	3.3568	0.1829	TECH	31	335	3.1002	0.1116	3.1195	0.6118	WINE	135	231	3.5582	0.4150	7.0404	0.3335
581	SCOT		366	17.5801	1.1695	3.2728	0.1769	TEK	213	153	3.2555	0.1358	3.0903	0.2203	WINGS	366		3.4713	0.1802	3.9499	0.2211
582	SCRPT	96	270	3.0607	0.1119	3.3636	0.4549	TELL	146	220	4.0651	0.1735	5.0511	0.5513	WINK	227	139	2.7716	0.1282	3.2907	0.1732
583	SCRT	68	298	2.8627	0.3971	4.7374	0.2015	TER	366		2.9635	0.1410	2.4231	0.1085	WISC	185	181	1.6425	0.0465	1.7410	0.0560
584	SCT	130	236	4.0958	0.1830	3.5542	0.3687	TES	359	7	2.7796	0.1345	3.1575	0.1561	WMC	103	263	2.3432	0.0925	2.6432	0.1320
585	SCX	24	342	2.1003	0.0790	2.0338	0.0788	TESLA	308	58	1.7866	0.0544	2.9369	0.1546	WOLF		366	17.7296	1.1830	3.3975	0.1861
586	SDAO	202	164	1.6941	0.0478	3.5034	0.2011	TFL	366		2.8479	0.1385	3.8730	0.2095	WOMEN	319	47	3.8341	0.2040	3.8983	0.2203
587	SDC	77	289	3.1923	0.1184	5.4223	0.9221	TGC	268	98	2.1763	0.0828	10.5421	0.7451	WOP	15	351				
588	SDP	175	191	3.8793	0.2051	1.8806	0.0677	TGT	271	95	3.8021	0.2038	4.9015	0.2933	WORM	65	301	1.9645	0.0682	2.1844	0.0919
589	SDRN	325	41	2.2584	0.0928	5.1915	0.3107	THC	366		2.4535	0.1049	3.1662	0.1642	WRC	186	180	2.4217	0.0868	2.2162	0.1229
590	SEC		366	17.4875	1.1658	3.3692	0.1839	THNX		366					WRC*	15	351	2.3572	0.1014	2.7260	0.1262
591	SEED		366	3.2098	0.1563	3.3851	0.1851	THS	214	152	2.4146	0.0891	3.3195	0.2172	WRT	10	356				
592	SEEDS	5	361					TIA	156	210	2.1443	0.0835	2.3976	0.1048	WSX	362	4	2.2614	0.0976	4.4835	0.2469
593	SEL	5	361					TIC		366	9.2884	0.5951	3.0992	0.1601	WTC	366		3.7852	0.2059	4.8000	0.2809
594	SEN	104	262	3.1281	0.1497	2.2578	0.0982	TIE	317	49	3.7220	0.2012	2.9212	0.1420	WTT	94	272	2.2605	0.0697	2.3648	0.2185
595	SEND	365	1	3.2657	0.1708	4.3040	0.2397	TIME	366		2.5834	0.1190	4.3557	0.2441	X2	182	184	5.3894	0.2623	7.2155	0.6702
596	SEQ		366	3.2409	0.1680	3.2889	0.1669	TIPS	172	194	2.3836	0.1028	2.5140	0.1113	XAI		366	3.2309	0.1577	3.3839	0.1850
597	SFC	214	152	2.2139	0.0893	3.4490	0.1820	TIT	105	261	3.0566	0.1132	2.6726	0.2788	XAP	115	251	2.0823	0.0730	2.1626	0.0962
598	SFR		366	17.7909	1.1873	3.3758	0.1844	TIX	366		3.0563	0.1508	4.8183	0.2846	XAS	366		3.3951	0.1738	3.9637	0.2234
599	SFT		366					TKN	128	238	4.2527	0.1839	4.7609	0.5166	XAU	158	208	2.0277	0.0711	3.8274	0.2257
600	SGC	68	298	1.4519	0.0245	2.3686	0.2634	TKN*	77	289	2.5141	0.0816	1.7885	0.1681	XAUR	366		3.4969	0.2464	2.4046	0.1059

Table 17 Summary-list of the cryptocurrencies considered on the market analysis along 2018 (part 4 out of 5)

	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N	SYM	TradDays	nonTradDays	AlphaP	Sd.P	AlphaN	Sd.N
601	XBC	366		3.6332	0.1941	2.2170	0.0902	XLC	342	24	4.0241	0.2248	3.7091	0.1992	XUP	55	311	2.6179	0.0872	2.1313	0.2412
602	XBL	340	26	3.0821	0.1548	4.6282	0.2667	XLM	366		4.0871	0.2314	6.3271	0.3885	XVC	215	151	2.2676	0.0847	2.0678	0.0896
603	XBOT		366	17.4831	1.1655	3.2650	0.1758	XMCC	365	1	3.3451	0.1748	3.1728	0.1593	XVE	123	243	5.2947	0.2382	6.1101	0.7981
604	XBP	80	286	1.4651	0.0255	2.4618	0.2545	XMG	99	267	4.1682	0.1744	9.1032	1.3505	XVG	366		3.4347	0.1748	4.4130	0.2602
605	XBS	59	307	2.0480	0.0561	1.8991	0.2181	XMO	34	332	1.3356	0.1938	2.5994	0.0839	XVP	310	56	2.0702	0.0793	2.0579	0.0780
606	XBTS	131	235	2.7362	0.0977	2.8963	0.2682	XMR	366		4.2595	0.2334	4.3851	0.2589	XWC	366		2.4146	0.1043	3.2337	0.1656
607	XBY	212	154	2.0259	0.0744	3.5291	0.1906	XMY	366		3.2761	0.1669	4.8293	0.2854	XWT		366				
608	XC		366	3.1466	0.1514	3.3301	0.1814	XNA		366					XXX		366	3.2186	0.1569	3.3820	0.1849
609	XCE	135	231	1.9823	0.0716	2.2035	0.0902	XNC	13	353					XZC	366		4.2506	0.2371	3.1631	0.1621
610	XCI		366	3.2130	0.1561	3.3179	0.1805	XNG	82	284	1.8742	0.0615	1.7969	0.0622	YAC	120	246	2.7564	0.0973	4.5792	0.5659
611	XCN	187	179	2.5383	0.1099	3.6063	0.1999	XNN	170	196	1.8664	0.0605	1.6925	0.0546	YAY	100	266	3.9735	0.1615	3.8520	0.5489
612	XCO	7	359					XNX	116	250	3.4310	0.4109	6.0059	0.2752	YBC	3	363				
613	XCP	366		3.1075	0.1575	3.1107	0.1543	XP	283	83	1.7033	0.0505	1.7875	0.0600	YES	328	38	4.0707	0.2124	3.5891	0.2066
614	XCPO	133	233	2.3355	0.0919	3.0914	0.1680	XPB		366	17.5686	1.1716	3.3802	0.1847	YMC	64	302	1.5903	0.0319	1.7279	0.1486
615	XCR		366	17.2732	1.1507	3.3819	0.1849	XPD	209	157	3.6611	0.2029	3.5781	0.1851	YOC	328	38	4.0971	0.2296	3.1495	0.1585
616	XCRE	2	364					XPH		366	17.3513	1.1562	3.2646	0.1758	YOVI	352	14	1.3372	0.0257	1.3856	0.0277
617	XCT		366					XPM	366		3.0802	0.1582	4.9957	0.2876	YOYOW	366		4.7367	0.2642	3.7814	0.2159
618	XCXT	3	363					XPO	2	364					ZAP	272	94	2.5863	0.1157	2.5894	0.1191
619	XDB	48	318	4.5513	0.1918	5.6562	0.9709	XPOKE		366					ZBC	233	133	2.0570	0.0825	2.0933	0.0769
620	XDE2		366					XPRO	2	364					ZCC		366	18.4054	1.2307	3.3659	0.1836
621	XDN	366		4.2829	0.2440	4.3962	0.2497	XPS	183	183	1.7094	0.0513	2.9350	0.1463	ZCG	95	271	1.7321	0.0535	1.7187	0.0537
622	XDP		366	17.5904	1.1731	3.3649	0.1836	XPT	29	337	2.1956	0.0643	3.1541	0.4817	ZCL	366		3.1634	0.1582	3.2894	0.1711
623	XDQ		366	17.1052	1.1388	3.2823	0.1771	XPTX	4	362					ZEC	366		3.6219	0.1917	9.0239	0.5997
624	XEL	366		4.2754	0.2358	3.3357	0.1776	XPY	80	286	6.7310	0.3099	5.1391	0.8449	ZECD	293	73	3.0174	0.1345	4.0897	0.2602
625	XEM	366		4.2576	0.2339	3.9187	0.2226	XQN	98	268	3.7564	0.4727	4.1995	0.1756	ZED		366	3.2108	0.1563	3.3740	0.1843
626	XEN		366					XRA	123	243	2.6395	0.0922	1.9418	0.1332	ZEIT	235	131	3.2676	0.1396	3.7169	0.2690
627	XFC		366					XRE	365	1	2.9381	0.1449	2.5652	0.1145	ZEN	366		3.2078	0.1602	3.1038	0.1586
628	XFT	274	92	3.0738	0.1478	3.4411	0.1878	XRL	115	251	2.7721	0.0982	2.5039	0.2378	ZENI	243	123	6.3276	0.3835	3.3891	0.1816
629	XG		366	17.1788	1.1412	3.2603	0.1760	XRP	366		3.0906	0.1537	5.1466	0.3082	ZER	365	1	2.8882	0.1385	3.4781	0.1847
630	XGB	14	352					XSEED		366	3.2270	0.1575	3.3345	0.1812	ZET	164	202	1.7144	0.0422	2.7804	0.2003
631	XGOX	357	9	1.8084	0.0555	1.7997	0.0644	XSI		366	3.2176	0.1568	3.3108	0.1794	ZET2	1	365				
632	XGR	84	282	2.1665	0.0844	2.2935	0.0978	XSP	7	359					ZLQ	126	240	3.0623	0.1153	3.0276	0.2990
633	XHI	228	138	2.9289	0.1201	2.8149	0.1746	XSPEC	366		3.7679	0.2075	3.7006	0.1970	ZNE	54	312	1.7450	0.0402	3.6163	0.5578
634	XID		366					XST	366		2.9520	0.1476	3.8248	0.2044	ZNY	47	319	1.5994	0.0323	1.8481	0.1851
635	XID*	31	335	1.4470	0.0239	1.5195	0.1299	XSTC		366					ZOI	273	93	2.1995	0.0877	3.7421	0.2050
636	XIN	362	4	2.1267	0.0880	2.1752	0.0827	XT	114	252	5.3853	0.2448	11.1155	1.5079	ZOOM	42	324	6.2526	0.2808	5.3396	1.0849
637	XIN*	289	77	1.3020	0.0249	1.4099	0.0277	XTC		366	17.3027	1.1528	3.4022	0.1864	ZRC	366		6.7926	0.4379	3.4593	0.1779
638	XIOS	124	242	3.1461	0.1203	3.7190	0.3925	XTO	20	346	2.9752	0.1051	6.1518	1.4289	ZRX	366		4.2963	0.2513	5.1588	0.2986
639	XJO	76	290	3.4072	0.1305	4.1292	0.6137	XTZ	233	133	3.2951	0.1418	2.7729	0.1739	ZSC	366		2.4806	0.1094	3.4605	0.1819
640	XLB		366	3.1836	0.1544	3.2701	0.1762	XUC	366		3.7465	0.1993	3.4375	0.1837	ZSE	274	92	2.2122	0.0864	2.9232	0.1479
641	XBC	366		3.6332	0.1941	2.2170	0.0902	XLC	342	24	4.0241	0.2248	3.7091	0.1992	ZUR	107	259	3.8970	0.1607	4.8615	0.6031
642	XBL	340	26	3.0821	0.1548	4.6282	0.2667	XLM	366		4.0871	0.2314	6.3271	0.3885	ZXT		366				
643	XBOT		366	17.4831	1.1655	3.2650	0.1758	XMCC	365	1	3.3451	0.1748	3.1728	0.1593	ZYD	85	281	3.4086	0.1304	3.8671	0.5734

Table 18 Summary-list of the cryptocurrencies considered on the market analysis along 2018 (part 5 out of 5)