# Complex network precursors of crashes and critical events in the cryptocurrency market

Andrii O. Bielinskyi and Vladimir N. Soloviev[0000-0002-4945-202X]

Kryvyi Rih State Pedagogical University, 54, Gagarin Ave., Kryvyi Rih, 50086, Ukraine
{krivogame, vnsoloviev2016}@gmail.com

**Abstract.** This article demonstrates the possibility of constructing indicators of critical and crash phenomena in the volatile market of cryptocurrency. For this purpose, the methods of the theory of complex networks have been used. The possibility of constructing dynamic measures of network complexity behaving in a proper way during actual pre-crash periods has been shown. This fact is used to build predictors of crashes and critical events phenomena on the examples of all the patterns recorded in the time series of the key cryptocurrency Bitcoin, the effectiveness of the proposed indicators-precursors of these falls has been identified.

**Keywords:** Cryptocurrency, Bitcoin, complex system, complex networks, measures of complexity, crash, critical events, indicator-precursor.



## 1 Introduction

The instability of global financial systems with regard to normal and natural disturbances of the modern market and the presence of poorly foreseeable financial crashes indicate, first of all, the crisis of the methodology of modeling, forecasting and interpretation of modern socio-economic realities. The doctrine of the unity of the scientific method states that for the study of events in socio-economic systems the same methods and criteria as those used in the study of natural phenomena are applicable. Significant success has been achieved within the framework of interdisciplinary approaches and the theory of self-organization – synergetics. The modern paradigm of synergetics is a complex paradigm associated with the possibility of direct numerical simulation of the processes of complex systems evolution, most of which have a network structure, or one way or another can be reduced to the network. The theory of complex networks studies the characteristics of networks, taking into account not only their topology, but also statistical properties, the distribution of weights of individual nodes and edges, the effects of dissemination of information, robustness, etc. [1-4].

Complex systems are systems consisting of a plurality of interacting agents possessing the ability to generate new qualities at the level of macroscopic collective behavior, the manifestation of which is the spontaneous formation of noticeable temporal, spatial, or functional structures. As simulation processes, the application of quantitative methods involves measurement procedures, where importance is given to complexity measures. I. Prigogine notes that the concepts of simplicity and complexity are relativized in the pluralism of the languages descriptions, which also determines the plurality of approaches to the quantitative description of the complexity phenomenon [5]. Therefore, we will continue to study Prigogine's manifestations of the system complexity, using the current methods of quantitative analysis to determine the appropriate measures of complexity.

The key idea here is the hypothesis that the complexity of the system before the crashes and the actual periods of crashes must change. This should signal the corresponding degree of complexity if they are able to quantify certain patterns of a complex system. Significant advantage of the introduced measures is their dynamism, that is, the ability to monitor the change in time of the chosen measure and compare it with the corresponding dynamics of the output time series. This allowed us to compare the critical changes in the dynamics of the system, which is described by the time series, with the characteristic changes of concrete measures of complexity. It turned out that quantitative measures of complexity respond to critical changes in the dynamics of a complex system, which allows them to be used in the diagnostic process and prediction of future changes.

Cryptocurrency market is a complex, self-organized system, which in most cases can be considered either as a complex network of market agents, or as an integrated output signal of such a network – a time series, for example, prices of individual cryptocurrency. Moreover, in the cryptocurrency market, to some extent, the blockchain technology is tested in general. Thus the cryptocurrency prices exhibit such complex volatility characteristics as nonlinearity and uncertainty, which are difficult to forecast and any results obtained are uncertain. Therefore, cryptocurrency price prediction remains a huge challenge.

Unfortunately, the existing nowadays classical econometric [6] and modern methods of prediction of crisis phenomena based on machine learning methods [7-11] do not have sufficient accuracy and reliability of prediction.

Thus, lack of reliable models of prediction of time series for the time being will update the construction of at least indicators which warn against possible critical phenomena or trade changes etc. This work is dedicated to the construction of such indicators-precursors based on the theory of complex networks and adapt them in order to study the critical and crash phenomena of cryptomarket.

The paper is structured as follows. Section 2 describes previous studies in these fields. Section 3 presents classification of crashes and critical events on the Bitcoin market during the entire period (16.07.2010 – 08.12.2018). Network measures of complexity and their effectiveness as indicators of cryptomarket crashes are presented in Section 4. And finally, we discuss our results in Section 5.

## 2 Analysis of previous studies

Throughout the existence of Bitcoin, its complexity became much larger. Crashes and critical events that took place on this market as well as the reasons that led to them, did not go unheeded. We determined that there are a lot of articles and papers on that topic which we will demonstrate.

Donier and Bouchaud [12] found that the market microstructure on Bitcoin exchanges can be used to anticipate illiquidity issues in the market, which lead to abrupt crashes. They investigate Bitcoin liquidity based on order book data and, out of this, accurately predict the size of price crashes.

Taking to the account studies on network analysis we can notice different papers on this topic [13-15]. Di Francesco Maesa et al. [13] have performed on the users' graph inferred from the Bitcoin blockchain, dumped in December 2015, so after the occurrence of the exponential explosion in the number of transactions. Researchers first present the analysis assessing classical graph properties like densification, distance analysis, degree distribution, clustering coefficient, and several centrality measures. Then, they analyze properties strictly tied to the nature of Bitcoin, like rich-get-richer property, which measures the concentration of richness in the network. Alexandre Bovet et al. [14] analyzed the evolution of the network of Bitcoin transactions among users and built network-based indicators of Bitcoin bubbles.

Authors [15] consider the history of Bitcoin and transactions in it. Using this dataset, they reconstruct the transaction network among users and analyze changes in the structure of the subgraph induced by the most active users. Their approach is based on the unsupervised identification of important features of the time variation of the network. Applying the widely used method of principal component analysis to the matrix constructed from snapshots of the network at different times, they show how changes in the network accompany significant changes in the price of Bitcoin.

Separately, it is necessary to highlight the work of Didier Sornette [16; 17], who built a precursor of crashes based on the generation of so-called log-periodic oscillations by the pre-crashing market. However, the actual collapse point is still badly predicted.

Thus, construction of indicators-precursors of critical and crash phenomena in the cryptocurrency market remains relevant.

## 3 Data

Bitcoin, despite its uncertain future, continues to attract investors, crypto-enthusiasts, and researchers. Being historically proven, popular and widely used cryptocurrency for the whole existence of cryptocurrencies in general, Bitcoin began to produce a lot of news and speculation, which began to determine its future life. Similar discussions began to lead to different kinds of crashes, critical events, and bubbles, which professional investors and inexperienced users began to fear. Thus, we advanced into action and set the tasks:

1. Classification of such bubbles, critical events and crashes.
2. Construction of such indicators that will predict crashes, critical events in order to give investors and ordinary users the opportunity to work in this market.

At the moment, there are various research works on what crises and crashes are and how to classify such interruptions in the market of cryptocurrencies. Taking into account the experience of previous researchers [18-21], we have created our classification of such leaps and falls, relying on Bitcoin time series during the entire period (16.07.2010 – 08.12.2018) of verifiable fixed daily values of the Bitcoin price (BTC) (https://finance.yahoo.com/cryptocurrencies).

For our classification, crashes are short, time-localized drops, with strong losing of price per each day, which are formed as a result of the bubble. Critical events are those falls that could go on for a long period of time, and at the same time, they were not caused by a bubble. The bubble is an increasing in the price of the cryptocurrencies that could be caused by certain speculative moments. Therefore, according to our classification of the event with number (1, 3-6, 9-11, 14, 15) are the crashes that are preceded by the bubbles, all the rest – critical events. More detailed information about crises, crashes and their classification in accordance with these definitions is given in the Table 1.

**Table 1.** BTC Historical Corrections. List of Bitcoin major corrections ≥ 20%

| No. | Time | Days in correction | Bitcoin High Price, $ | Bitcoin Low Price, $ | Decline, % | Decline, $ |
|---|---|---|---|---|---|---|
| 1 | 07.06.2011-10.06.2011 | 4 | 29.60 | 14.65 | 50 | 15.05 |
| 2 | 15.01.2012-16.02.2012 | 33 | 7.00 | 4.27 | 39 | 2.73 |
| 3 | 15.08.2012-18.08.2012 | 4 | 13.50 | 8.00 | 40 | 5.50 |
| 4 | 08.04.2013-15.04.2013 | 8 | 230.00 | 68.36 | 70 | 161.64 |
| 5 | 04.12.2013-18.12.2013 | 15 | 1237.66 | 540.97 | 56 | 696.69 |
| 6 | 05.02.2014-25.02.2014 | 21 | 904.52 | 135.77 | 85 | 768.75 |
| 7 | 12.11.2014-14.01.2015 | 64 | 432.02 | 164.91 | 62 | 267.11 |
| 8 | 11.07.2015-23.08.2015 | 44 | 310.44 | 211.42 | 32 | 99.02 |
| 9 | 09.11.2015-11.11.2015 | 3 | 380.22 | 304.70 | 20 | 75.52 |
| 10 | 18.06.2016-21.06.2016 | 4 | 761.03 | 590.55 | 22 | 170.48 |
| 11 | 04.01.2017-11.01.2017 | 8 | 1135.41 | 785.42 | 30 | 349.99 |
| 12 | 03.03.2017-24.03.2017 | 22 | 1283.30 | 939.70 | 27 | 343.60 |
| 13 | 10.06.2017-15.07.2017 | 36 | 2973.44 | 1914.08 | 36 | 1059.36 |
| 14 | 16.12.2017-22.12.2017 | 7 | 19345.5 | 13664.96 | 29 | 5680.53 |
| 15 | 13.11.2018-26.11.2018 | 14 | 6339.17 | 3784.59 | 40 | 2554.58 |

Accordingly, during this period in the Bitcoin market, many crashes and critical events shook it. Thus, considering them, we emphasize 15 periods on Bitcoin time series, whose falling we predict by our indicators, relying on normalized returns and volatility, where normalized returns are calculated as

$$g(t) = \ln X(t+\Delta t) - \ln X(t) \cong [X(t+\Delta t) - X(t)] / X(t),$$

and volatility as $V_T(t) = \frac{1}{n}\sum_{t'=t}^{t+n-1} |g(t')|$ Besides, considering that $g(t)$ should be more than the $\pm 3\sigma$, where $\sigma$ is a mean square deviation.

Calculations were carried out within the framework of the algorithm of a moving window. For this purpose, the part of the time series (window), for which there were calculated measures of complexity, was selected, then the window was displaced along the time series in a one-day increment and the procedure repeated until all the studied series had exhausted. Further, comparing the dynamics of the actual time series and the corresponding measures of complexity, we can judge the characteristic changes in the dynamics of the behavior of complexity with changes in the cryptocurrency. If this or that measure of complexity behaves in a definite way for all periods of crashes, for example, decreases or increases during the pre-crashes period, then it can serve as an indicator or precursor of such a crashes phenomenon.

Calculations of measures of complexity were carried out both for the entire time series, and for a fragment of the time series localizing the crash. In the latter case, fragments of time series of the same length with fixed points of the onset of crashes or critical events were selected and the results of calculations of complexity measures were compared to verify the universality of the indicators.

In the Fig. 1 output Bitcoin time series, normalized returns $g(t)$, and volatility $V_T(t)$ calculated for the window size 100 are presented.

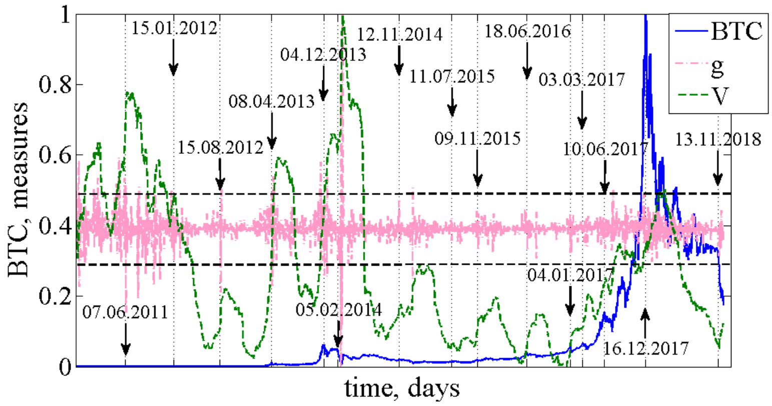


**Fig. 1.** The standardized dynamics, returns $g(t)$, and volatility $V_T(t)$ of BTC/USD daily values. Horizontal dotted lines indicate the $\pm 3\sigma$ borders. The arrows indicate the beginning of one of the crashes or the critical events

From Fig. 1 we can see that during periods of crashes and critical events normalized profitability $g$ increases considerably in some cases beyond the limits $\pm 3\sigma$. This indicates about deviation from the normal law of distribution, the presence of the "heavy tails" in the distribution $g$, characteristic of abnormal phenomena in the market. At the same time volatility also grows. These characteristics serve as indicators of critical and collapse phenomena as they react only at the moment of the above mentioned phenomena and don't give an opportunity to identify the corresponding abnormal phenomena in advance. In contrast, the indicators described below respond to critical and collapse phenomena in advance. It enables them to be used as indicators-precursors of such phenomena and in order to prevent them.

## 4 Complex network indicators

The most commonly used methods for converting time sequences to the corresponding networks are recurrent [22], visibility graph [23] and correlation [24]. In the first case, the recurrence diagram is transformed into an adjacency matrix, on which the spectral and topological characteristics of the graph are calculated. The algorithm of the visibility graph is realized as follows. Take a time series $Y(t) = [y_1, y_2, ..., y_n]$ of length $N$. Each point in the time series data can be considered as a vertex in an associated network, and the edge connects two vertices if two corresponding data points can "see' each other from the corresponding point in the time series. Formally, two values of the series $y_a$ (at the time of time $t_a$) and $y_b$ (at the time of time $t_b$) are connected, if for any other value ($y_c$, $t_c$), which is placed between them (i. e., $t_a < t_c < t_b$), the condition is satisfied:

$$y_c < y_a + (y_b - y_a)\frac{t_c - t_a}{t_b - t_a}$$

To construct and analyze the properties of a correlation graph, we must form a correlation matrix from the set of cryptocurrencies (as is done in Section 7), and from it we must pass to the matrix of adjacency. To do this, you must enter a value which, for the correlation field, will be the distance between the correlated assets. Such a distance may be dependent on the correlation coefficients $c_{ij}$ of the value $x(i, j) = (2(1-c_{ij}))^{1/2}$. So, if the correlation coefficient between the two assets is significant, the distance between them is small, and, starting from some critical value, assets can be considered bound on the graph.

For constructed graph methods described above, one can calculate spectral and topological properties. We will show that some of them serve as a measure of the complexity of the system, and the dynamics of their changes allows us to build predictors of crashes or critical events in the financial markets.

Spectral theory of graphs is based on algebraic invariants of a graph – its spectra. The spectrum of graph $G$ is the set of eigenvalues $S_p(G)$ of a matrix corresponding to a given graph. For adjacency matrix $A$ of a graph, there exists an characteristic polynomial $|\lambda I - A|$, which is called the characteristic polynomial of a graph $P_G(\lambda)$. The eigenvalues of the matrix $A$ (the zeros of the polynomial $|\lambda I - A|$) and the spectrum of the matrix $A$ (the set of eigenvalues) are called respectively their eigenvalues $\lambda$ and the spectrum $S_p(G)$ of graph $G$. The eigenvalues of the matrix $A$ satisfy the equality $A\bar{x} = \lambda\bar{x}$ ($\bar{x}$ – non-zero vector). Vectors $\bar{x}$ satisfying this equality are called eigenvectors of the matrix $A$ (or the graph $G$) corresponding to their eigenvalues.

From a multiplicity of spectral and topological measures we will choose only two – the maximum eigenvalue $\lambda_{\max}$ of the adjacency matrix and Average path Length (ApLen). For a connected network of $N$ nodes, the ApLen is equal

$$< l >= \frac{2}{n(N-1)}\sum_{i>j} l_{ij},$$

where $l_{ij}$ – the length of the shortest path between the nodes $i$ and $j$.

Fig. 2 demonstrates the asymmetric response of the spectral and topological measures of network complexity. For the complete series, the calculation parameters are as follows: window width 100, step is 1 day. For local measures, the length of the fragment is 150, the width of the window is 50 and the step is 1 day.

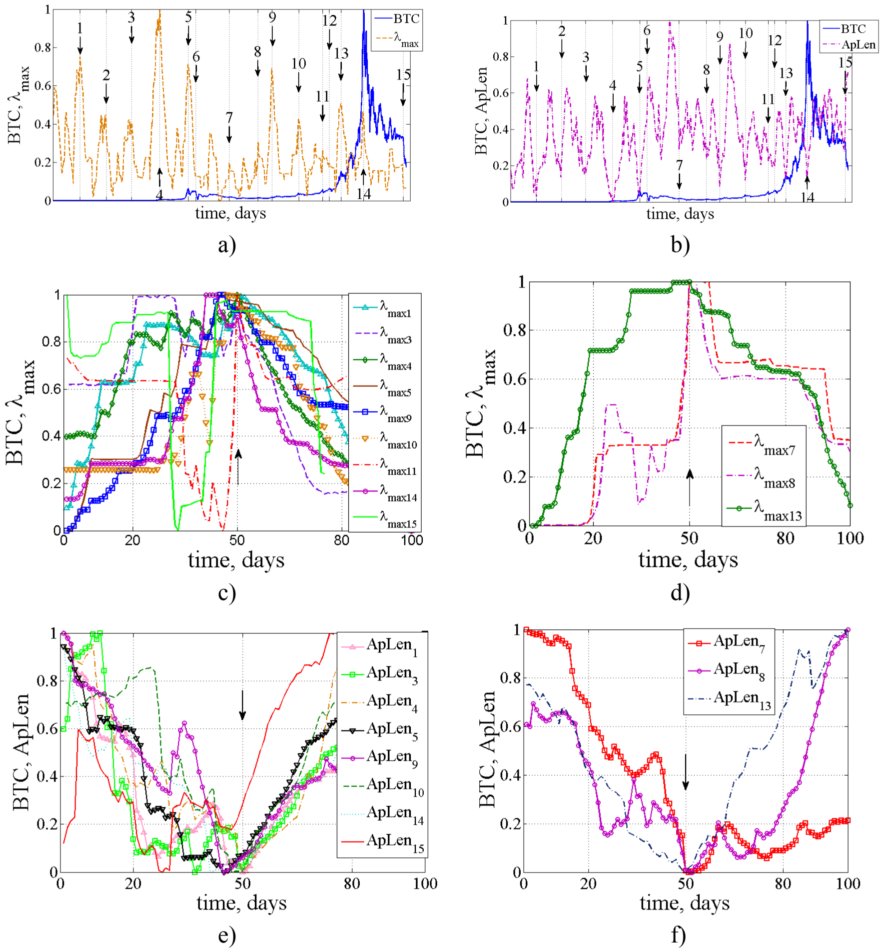


**Fig. 2.** Visibility graph dynamics of network measures $\lambda_{max}$ (a), ApLen (b) for all Bitcoin time series. Dynamics of network measures for local crashes (c, e) and crisis events (d, f)

The maximum actual value of the adjacency matrix of the visibility graph both for Bitcoin as a whole and for isolated segments of time series containing a crash and critical phenomenon, takes maximum value. It corresponds to the maximum complexity of the system. An especial state of the system leads to a decrease in complexity, and, accordingly, to a decrease in value $\lambda_{max}$. Average length of the path on the graph (ApLen) is, on the contrary, minimal for complex systems and increases with the randomization of the system. Such increase during pre-crash and pre-critical states as well as reduce $\lambda_{max}$ are indicators-precursors of the above mentioned states. You can choose other spectral and topological measures from the calculated ones, e.g. the maximum degree of the vertex and the diameter of the graph, algebraic connectivity and centrality, etc. Network measures of complexity, thus, are the most universal and informative and have obvious advantages in the selection of indicators of special states.

## 5 Conclusions

Consequently, in this paper, we have shown that monitoring and prediction of possible critical changes on cryptocurrency is of paramount importance. As it has been shown by us, the theory of complex networks has a powerful toolkit of methods and models for creating effective indicators-precursors of crashes and critical phenomena. In this paper, we have explored the possibility of using the network measures of complexity to detect dynamical changes in a complex time series. We have shown that the measures that have been used can indeed be effectively used to detect abnormal phenomena for the time series of Bitcoin.

## References


1. Halvin, S., Cohen, R.: Complex networks. Structure, robustness and function. Cambridge University Press, New York (2010)
2. Albert, R., Barabási, A.-L.: Statistical Mechanics of Complex Networks. Rev. Mod. Phys. **74**, 47–97 (2002). doi:10.1103/RevModPhys.74.47
3. Newman, M., Barabási A.-L., Watts D.J.: The Structure and Dynamics of Networks. Princeton University Press, Princeton (2006)
4. Newman, M.E.J.: The Structure and Function of Complex Networks. SIAM Reviews. **45**(2), 167–256 (2003). doi:10.1137/S003614450342480
5. Nikolis, G., Prigogine, I.: Exploring Complexity: An Introduction. St. Martin's Press, New York (1989)
6. Andrews, B., Calder, M., Davis, R.A.: Maximum Likelihood Estimation for α-Stable Autoregressive Processes. The Annals of Statistics. **37**(4), 1946–1982 (2009). doi:10.1214/08-AOS632
7. Shah, D., Zhang, K.: Bayesian regression and Bitcoin. In: 2014 52nd Annual Allerton Conference on Communication, Control, and Computing (Allerton), Monticello, 30 Sept.-3 Oct. 2014. doi:10.1109/ALLERTON.2014.7028484
8. Chen, T., Guestrin, C.: XGBoost: A Scalable Tree Boosting System. In: KDD '16 Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, August 13-17, 2016, pp. 785-794 (2016). doi:10.1145/2939672.2939785
9. Alessandretti, L., ElBahrawy, A., Aiello, L.M., Baronchelli, A.: Machine Learning the Cryptocurrency Market. https://ssrn.com/abstract=3183792 (2018). doi:10.2139/ssrn.3183792. Accessed 15 Sep 2018
10. Guo, T., Antulov-Fantulin, N.: An experimental study of Bitcoin fluctuation using machine learning methods. arXiv:1802.04065v2 [stat.ML]. https://arxiv.org/pdf/1802.04065.pdf (2018). Accessed 15 Sep 2018

11. Peng Y., Albuquerque, P.H.M., de Sá, J.M.C., Padula, A.J.A., Montenegro, M.R: The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with Support Vector Regression. Expert Systems with Applications. **97**, 177–192 (2018). doi:10.1016/j.eswa.2017.12.004
12. Donier, J., Bouchaud J.-P.: Why Do Markets Crash? Bitcoin Data Offers Unprecedented Insights. PLoS ONE 10(10): e0139356 (2015). doi:10.1371/journal.pone.0139356
13. Di Francesco Maesa, D., Marino, A., Ricci, L.: Data-driven analysis of Bitcoin properties: exploiting the users graph. International Journal of Data Science and Analytics. **6**(1), 63–80 (2018). doi:10.1007/s41060-017-0074-x
14. Bovet, A., Campajola, C., Lazo, J.F., Mottes, F., Pozzana, I., Restocchi, V., Saggese, P., Vallarano, N., Squartini, T., Tessone, C.J.: Network-based indicators of Bitcoin bubbles. arXiv:1805.04460v1 [physics.soc-ph]. https://arxiv.org/pdf/1805.04460 (2018). Accessed 11 Sep 2018
15. Kondor, D., Csabai, I., Szüle, J., Pósfai, M., Vattay, G.: Inferring the interplay of network structure and market effects in Bitcoin. New Journal of Physics. **16**, 125003 (2014). doi:10.1088/1367-2630/16/12/125003
16. Wheatley, S., Sornette, D., Huber, T., Reppen, M., Gantner, R.N.: Are Bitcoin Bubbles Predictable? Combining a Generalized Metcalfe's Law and the LPPLS Model. Swiss Finance Institute Research Paper No. 18-22. https://ssrn.com/abstract=3141050 (2018). doi:10.2139/ssrn.3141050. Accessed 15 Sep 2018
17. Gerlach, J-C., Demos, G., Sornette, D.: Dissection of Bitcoin's Multiscale Bubble History from January 2012 to February 2018. arXiv:1804.06261v2 [econ.EM]. https://arxiv.org/pdf/1804.06261 (2018). Accessed 15 Sep 2018
18. Soloviev, V., Belinskij, A.: Methods of nonlinear dynamics and the construction of cryptocurrency crisis phenomena precursors. In: Ermolayev, V., Suárez-Figueroa, M.C., Yakovyna, V., Kharchenko, V., Kobets, V., Kravtsov, H., Peschanenko, V., Prytula, Y., Nikitchenko, M., Spivakovsky, A. (eds.) Proceedings of the 14th International Conference on ICT in Education, Research and Industrial Applications. Integration, Harmonization and Knowledge Transfer. Volume II: Workshops, Kyiv, Ukraine, May 14-17, 2018. CEUR Workshop Proceedings. **2014**, 116–127. http://ceur-ws.org/Vol-2104/paper_175.pdf (2018). Accessed 30 Sep 2018
19. Casey, M.B.: Speculative Bitcoin Adoption/Price Theory. https://medium.com/@mcasey0827/speculative-bitcoin-adoption-price-theory-2eed48ecf7da (2016). Accessed 25 Sep 2018
20. McComb, K.: [2018] Bitcoin Crash: Analysis of 8 Historical Crashes and What's Next. https://blog.purse.io/bitcoin-crash-e112ee42c0b5 (2018). Accessed 25 Sep 2018
21. Amadeo, K.: Stock Market Corrections Versus Crashes and How to Protect Yourself: How You Can Tell If It's a Correction or a Crash. https://www.thebalance.com/stock-market-correction-3305863 (2018). Accessed 25 Sep 2018
22. Donner, R.V., Small, M., Donges, J.F., Marwan, N., Zou, Y., Xiang, R., Kurths, J.: Recurrence-based time series analysis by means of complex network methods. International Journal of Bifurcation and Chaos. **21**(04), 1019–1046 (2011). doi:10.1142/S0218127411029021
23. Lacasa, L., Luque, B., Ballesteros, F., Luque, J., Nuño, J.C.: From time series to complex networks: The visibility graph. Proceedings of the National Academy of Sciences of the United States of America. **105**(13), 4972–4975 (2008). doi:10.1073/pnas.0709247105
24. Burnie, A.: Exploring the Interconnectedness of Cryptocurrencies using Correlation Networks. arXiv:1806.06632 [q-fin.CP]. https://arxiv.org/pdf/1806.06632 (2018). Accessed 25 Sep 2018