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QUANTUM ECONOPHYSICAL PRECURSORS OF CRYPTOCURRENCY CRASHES

This article demonstrates the possibility of constructing indicators of critical and crash phenomena in the volatile market of cryptocurrency.

The possibility of constructing dynamic measures of complexity as quantum econophysical 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. From positions, attained by modern theoretical physics the concept of economic Planck's constant has been proposed.

The theory on the economic dynamic time series related to the cryptocurrencies market has been approved. Then, combining the empirical cross-correlation matrix with the Random Matrix Theory, we mainly examine the statistical properties of cross-correlation coefficient, the evolution of the distribution of eigenvalues and corresponding eigenvectors of the global cryptocurrency market using the daily returns of cryptocurrencies price time series all over the world from 2013 to 2018.

The result has indicated that the largest eigenvalue reflects a collective effect of the whole market, and is very sensitive to the crash phenomena. It has been shown that both the introduced economic mass and the largest eigenvalue of the matrix of correlations can act like quantum indicators-predictors of falls in the market of cryptocurrencies.

Keywords: *Cryptocurrency, Bitcoin, complex system, measures of complexity, crash, critical events, complex networks, quantum econophysics, Heisenberg uncertainty principle, Random Matrix Theory, indicator-precursor.*

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 descriptions of languages, 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. The research on cryptocurrency price fluctuations being carried out internationally is made more complex by the interplay due to many factors – including market supply and demand, the US dollar exchange rate, stock market state, the influence of crime and the shadow market, and fiat money regulator pressure – that introduces a high level of noise into the cryptocurrency data. 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 [6-8] and modern methods of prediction of crisis phenomena based on machine learning methods [9-16] 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 complexity.

In this paper, we consider some of the informative measures of complexity 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). In Section 4, new quantum indicators of critical and crash phenomena are introduced using the Heisenberg uncertainty principle and the Random Matrix Theory.

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 [17] 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.

F. Bariviera [18] demonstrates the dynamics of the intraday price of 12 cryptocurrencies. By using the complexity-entropy causality plane, authors discriminate three different dynamics in the data set. Another paper [19] compares the time-varying weak-form efficiency of Bitcoin prices in terms of US dollars (BTC/USD) and euro (BTC/EUR) at a high-frequency level by using Permutation Entropy. Their research shows that BTC/USD and BTC/EUR markets have been demonstrating more information at the intraday level since the beginning of 2016, and BTC/USD market has been slightly more efficient than BTC/EUR during the same period. And moreover, their research shows that with the higher frequency we have less price efficiency.

Some papers like this one [20] demonstrate how recurrence plots and measures of recurrence quantification analysis can be used to study significant changes in complex dynamical systems due to a change in control parameters, chaos-order as well as chaos-chaos transitions. Tiago Santos et al. [21] discuss how to model activity in online collaboration websites, such as Stock Exchange Question and Answering portals because the success of these websites critically depends on the content contributed by its users. In this paper, they represent user activity as time series and perform an initial analysis of these time series to obtain a better understanding of the underlying mechanisms that govern their creation. For this purpose nonlinear modeling via recurrence plots was used, which gives more granular study and deeper understanding of nonlinear dynamics of governing activity of time series and explaining the activity in online collaboration websites.

Taking to the account studies on network analysis we can notice different papers on this topic [22-24]. Di Francesco Maesa et al. [22] 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. [23] analyzed the evolution of the network of Bitcoin transactions among users and built network-based indicators of Bitcoin bubbles.

In this article [24], authors 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 [25, 26], 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.

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 [26-30], 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.

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

$$g(t) = \ln X(t+\Delta t) - \ln X(t) \cong [X(t+\Delta t) - X(t)]/X(t). \quad (1)$$

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.

Table 1

BTC Historical Corrections. List of Bitcoin major corrections ≥ 20% since June 2011

№	Name	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	19345.49	13664.96	29	5680.53
15	13.11.2018-26.11.2018	14	6339.17	3784.59	40	2554.58

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

From Figure 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.

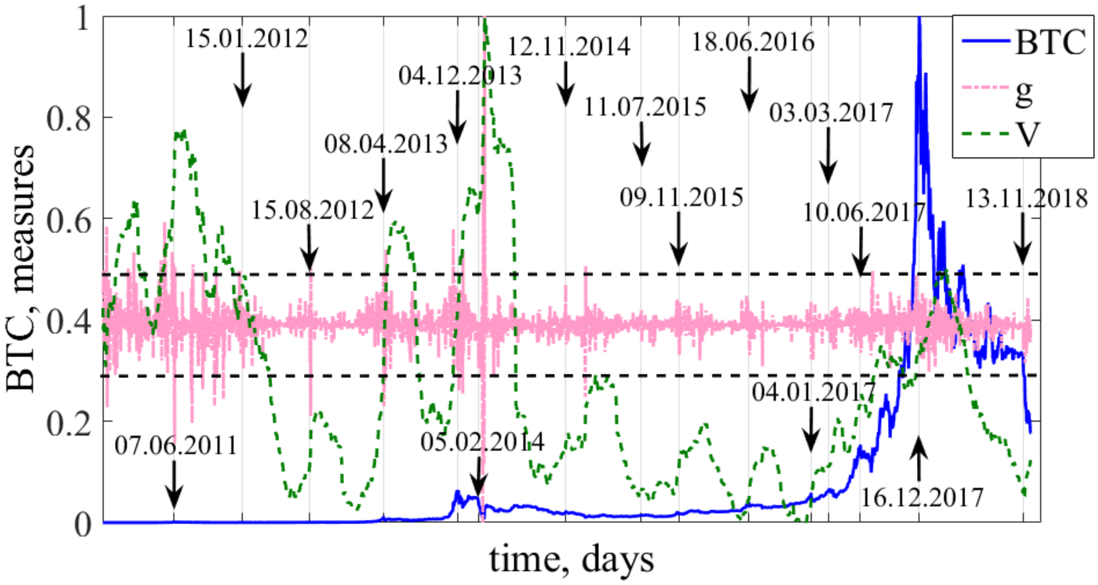


Fig. 1. The standardized dynamics, returns $g(t)$, and volatility $V_T(t)$ of BTC/USD daily values. Horizontal dotted lines indicate the $\pm 3\sigma$ borders. The arrows indicate the beginning of one of the crashes or the critical events

Quantum econophysics indicators

The attempts to create an adequate model of socio-economic critical events, which, as it has been historically proven, are almost permanent, were, are and will always be made. Actually, it is a super task impossible to solve. However, the potentially useful solutions, local in time or other socio-economic logistic coordinates, are possible. In fact, they have to be the object of interest for a real and effective economic science.

Econophysics is a young interdisciplinary scientific field, which developed and acquired its name at the end of the last century [31]. Quantum econophysics, a direction distinguished by the use of mathematical apparatus of quantum mechanics as well as its fundamental conceptual ideas and relativistic aspects, developed within its boundaries just a couple of years later, in the first decade of the 21st century [32-36].

According to classical physics, immediate values of physical quantities, which describe the system status, not only exist, but can also be exactly measured. Although non-relativistic quantum mechanics doesn't reject the existence of immediate values of classic physical quantities, it postulates that not all of them can be measured simultaneously (Heisenberg uncertainty ratio). Relativistic quantum mechanics denies the existence of immediate values for all kinds of physical quantities, and, therefore, the notion of system status seizes to be algoristic.

In this section, we will demonstrate the possibilities of quantum econophysics on the example of the application of the Heisenberg uncertainty principle and the Random Matrices Theory to the actual and debatable now market of cryptocurrencies.

Heisenberg uncertainty principle and economic analogues of basic physical quantities

In our paper [34] we have suggested a new paradigm of complex systems modeling based on the ideas of quantum as well as relativistic mechanics. It has been revealed that the use of quantum-mechanical analogies (such as the uncertainty principle, notion of the operator, and quantum measurement interpretation) can be applied to describing socio-economic processes. Methodological and philosophical analysis of fundamental physical notions and constants, such as time, space and spatial coordinates, mass, Planck's constant, light velocity from the point of view of modern theoretical physics provides an opportunity to search of adequate and useful analogues in socio-economic phenomena and processes.

The Heisenberg uncertainty principle is one of the cornerstones of quantum mechanics. The modern version of the uncertainty principle, deals not with the precision of a measurement and the disturbance it introduces, but with the intrinsic uncertainty any quantum state must possess, regardless of what measurement is performed [35, 36]. Recently, the study of uncertainty relations in general has been a topic of growing interest, specifically in the setting of quantum information and quantum cryptography, where it is fundamental to the security of certain protocols [37-39].

To demonstrate it, let us use the known Heisenberg's uncertainty ratio which is the fundamental consequence of non-relativistic quantum mechanics axioms and appears to be (e.g. [40]):

$$\Delta x \cdot \Delta v \geq \frac{\hbar}{2m_0}, \tag{2}$$

where Δx and Δv are mean square deviations of x coordinate and velocity v corresponding to the particle with (rest) mass m_0, $\hbar$ – Planck's constant. Considering values Δx и Δv to be measurable when their product reaches its minimum, we derive (from (1)):

$$m_0 = \frac{\hbar}{2 \cdot \Delta x \cdot \Delta v}, \tag{3}$$

i.e. mass of the particle is conveyed via uncertainties of its coordinate and velocity – time derivative of the same coordinate.

Economic measurements are fundamentally relative, are local in time, space and other socio-economic coordinates, and can be carried out via consequent and/or parallel comparisons "here and now", "here and there", "yesterday and today", "a year ago and now" etc.

Due to these reasons constant monitoring, analysis, and time series prediction (time series imply data derived from the dynamics of stock indices, exchange rates, cryptocurrencies prices, spot prices and other socio-economic indicators) becomes relevant for evaluation of the state, tendencies, and perspectives of global, regional, and national economies.

Suppose there is a set of *K* time series, each of *N* samples, that correspond to the single distance *T*, with an equal minimal time step $\Delta t_{\min}$:

$$X_i(t_n),\ t_n = \Delta t_{\min} n;\ n = 0,\ 1,\ 2,\ \ldots N-1;\ i = 1,\ 2,\ \ldots K. \tag{4}$$

To bring all series to the unified and non-dimensional representation, accurate to the additive constant, we normalize them, having taken a natural logarithm of each term of the series. Then consider that every new series $x_i(t_n)$ is a one-dimensional trajectory of a certain fictitious or abstract particle numbered i, while its coordinate is registered after every time span $\Delta t_{\min}$, and evaluate mean square deviations of its coordinate and speed in some time window $\Delta T = \Delta N \cdot \Delta t_{\min} = \Delta N,\ 1 << \Delta N << N$. The «immediate» speed of i particle at the moment t_n is defined by the ratio:

$$v_i\left(t_n\right) = \frac{x_i(t_{n+1}) - x_i(t_n)}{\Delta t_{\min}} = \frac{1}{\Delta t_{\min}} \ln \frac{X_i(t_{n+1})}{X_i(t_n)} \tag{5}$$

with variance D_{v_i} and mean square deviation Δv_i.

Keeping an analogy with (1) after some transformations we can write an uncertainty ratio for this trajectory [40]:

$$\frac{1}{\Delta t_{\min}}\left(< \ln^2 \frac{X_i(t_{n+1})}{X_i(t_n)} >_{n,\Delta N} - \left(< \ln \frac{X_i(t_{n+1})}{X_i(t_n)} >_{n,\Delta N} \right)^2 \right) \sim \frac{h}{m_i}, \tag{6}$$

where m_i – economic "mass" of an i series, h – value which comes as an economic Planck's constant.

Since the analogy with physical particle trajectory is merely formal, h value, unlike the physical Planck's constant $\hbar$, can, generally speaking, depend on the historical period of time, for which the series are taken, and the length of the averaging interval (e.g. economical processes are different in the time of crisis and recession), on the series number i etc. Whether this analogy is correct or not depends on particular series' properties.

In recent work [40], we tested the economic mass as an indicator of crisis phenomena on stock index data. In this work we will test the model for the cryptocurrency market on the example of the Bitcoin [41].

Obviously, there is a dynamic characteristic values m depending on the internal dynamics of the market. In times of crashes known marked by arrows in the Figures 2(a) and 2(b) mass m is significantly reduced in the pre-crash and pre-critical periods.

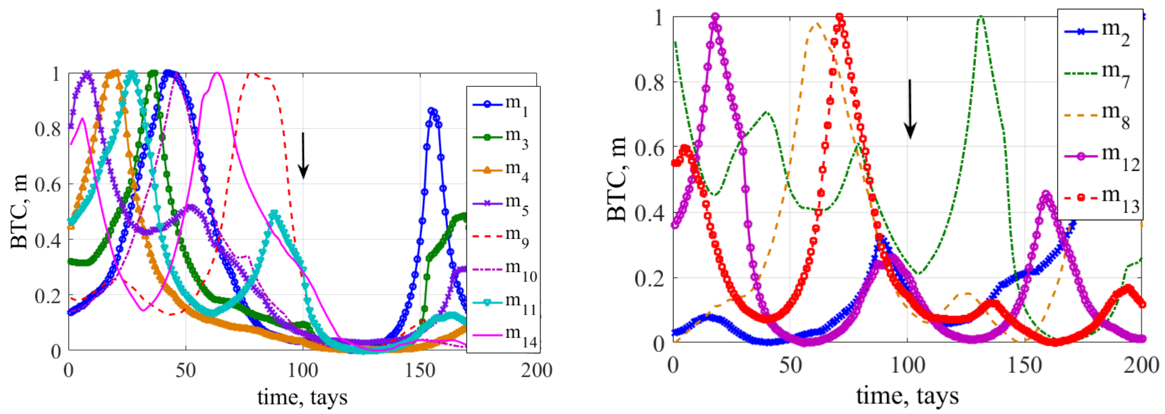


Fig. 2. Dynamics of measure m for local crashes (a) and critical events (b)

Obviously, that the value of m remains a good indicator-precursor even in this case. Value m is considerably reduced before a special market condition. The market becomes more volatile and prone to changes.

The following method of quantum econophysics is borrowed from nuclear physicists and is called Random Matrix Theory.

Random Matrix Theory and quantum indicators-predictors

Random Matrix Theory (RMT) developed in this context the energy levels of complex nuclei, which the existing models failed to explain (Wigner, Dyson, Mehta, and others [44-46]). Deviations from the universal predictions of RMT identify system specific, nonrandom properties of the system under consideration, providing clues about the underlying interactions.

Unlike most physical systems, where one relates correlations between subunits to basic interactions, the underlying "interactions" for the stock market problem are not known. Here, we analyze cross correlations between stocks by applying concepts and methods of random matrix theory, developed in the context of complex quantum systems where the precise nature of the interactions between subunits are not known.

RMT has been applied extensively in studying multiple financial time series [47-53].

Special databases have been prepared, consisting of cryptocurrency time series for a certain period of time. The largest number of cryptocurrencies 1047 contained a base of 456 days from 31.12.2017 to 15.09.2018, and the smallest (24 cryptocurrencies) contained a base of 1567 days, respectively, from 04.08.2013 to 15.09.2018 (https://coinmarketcap.com/all/views/all/). In order to quantify correlations, we first calculate the logarithmic return (1) of the i cryptocurrencies price series over a time scale $\Delta t = 1$ day. We calculate the pairwise cross-correlation coefficients between any two cryptocurrencies returns time series. for the largest database, a graphical representation of the pair correlation field is shown in the Figure 3a. For comparison, a map of correlations of randomly mixed time series of the same length is shown in Figure 3b.

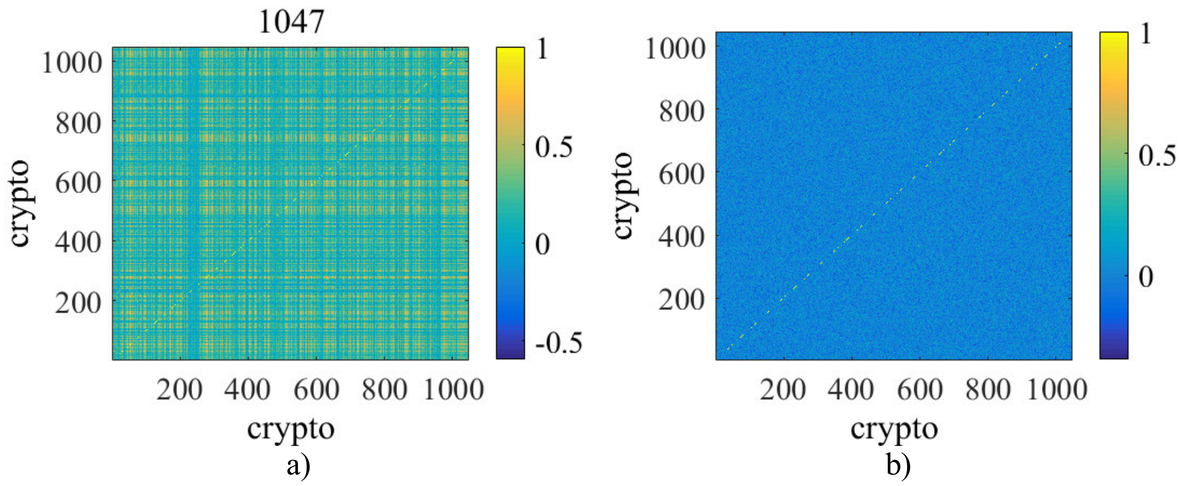


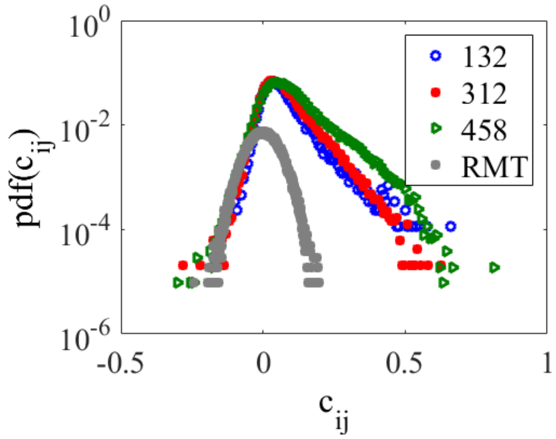
Fig. 3. Visualization of the field of correlations for the initial (a) and mixed (b) time series

For the correlation matrix C we can calculate its eigenvalues, $C = U\Lambda U^T$, where U denotes the eigenvectors, Λ is the eigenvalues of the correlation matrix, whose density $f_c(\lambda)$ is defined as follows, $f_c(\lambda) = \left(1/N\right) dn(\lambda)/d\lambda$. $n(\lambda)$ is the number of eigenvalues of C that are less than λ. In the limit $N \to \infty$, $T \to \infty$ and $Q = T/N \geq 1$ fixed, the probability density function $f_c(\lambda)$ of eigenvalues λ of the random correlation matrix M has a close form:

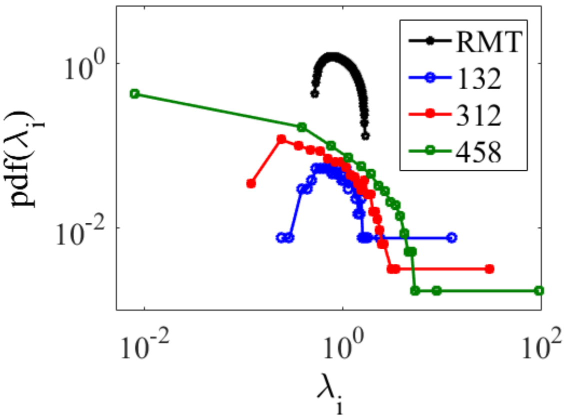
$$f_c(\lambda) = \frac{Q}{2\pi\sigma^2} \frac{\sqrt{(\lambda_{\max} - \lambda)(\lambda - \lambda_{\min})}}{\lambda} \tag{7}$$

with $\lambda \in [\lambda_{\min}, \lambda_{\max}]$, where $\lambda_{\min}^{\max}$ is given by $\lambda_{\min}^{\max} = \sigma^2\left(1 + 1/Q \pm 2\sqrt{1/Q}\right)$ and σ^2 is equal to the variance of the elements of matrix M.

We compute the eigenvalues of the correlation matrix C, $\lambda_{\max} = \lambda_1 > \lambda_2 > ... > \lambda_{15} = \lambda_{\min}$. The probability density functions (pdf) of paired correlation coefficients c_{ij} and eigenvalues λ_i for matrices of 132, 312, and 458 cryptocurrencies are presented in Figure 4. From Fig. 4a, it can be seen that the distribution functions for the paired correlation coefficients of the selected matrices differ significantly from the distribution function. described by the RMT. It can be seen that the crypto market has a significantly correlated, self-organized system (Fig. 4a) and the difference from the RMT of the case, the correlation coefficients exceed the value of 0.6-0.8 on “thick tails”. The distribution of the eigenvalues of the correlation matrix also differs markedly from the case of RMT In our case, only one-third of its own values refer to the RMT region.



a)



b)

Fig. 4 Comparison of distributions of the pair correlation coefficients (a) and eigenvalues of the correlation matrix (b) with those for RMT

Eigenvectors correspond to the participation ratio PR and its inverse participation ratio IPR $I^k = \sum_{l=1}^{N} \left[u_l^k\right]^4$, where u_l^k, $l = 1,...,N$ are the components of the eigenvector u^k (Fig. 5a). So PR indicates the number of eigenvector components that contribute significantly to that eigenvector. More specifically, a low IPR indicates that cryptocurrency contribute more equally. In contrast, a large IPR would imply that the factor is driven by the dynamics of a small number of cryptocurrencies. The irregularity of the influence of the eigenvalues of the correlation matrix is determined by the absorption ratio (AR), which is a cumulative risk measure $AR_n = \sum_{k=1}^{n} \lambda_k \Big/ \sum_{k=1}^{N} \lambda_k$ and indicates which part of the overall variation is described from the total number N of eigenvalues.

In Figure 5, within the framework of the algorithm of a moving window, comparative calculations of the distribution function of eigenvalues (b), IPR (c) and some measures of complexity (d) are presented. The difference in dynamics is due to the peculiarities of non-random correlations between the time series of individual assets. Under the framework of Random Matrix Theory, if the eigenvalues of the real time series differ from the prediction of RMT, there must exists hidden economic information in those deviating eigenvalues. For cryptocurrencies markets, there are several deviating eigenvalues in which the largest eigenvalue $\lambda_{\max}$ reflects a collective effect of the whole market. As for PR the differences from RMT appear at large and small λ values and are similar to the Anderson quantum effect of localization [54]. Under crashes conditions, the states at the edges of the distributions of eigenvalues are delocalized, thus identifying the beginning of the crash. This is evidenced by the results presented in Figure 5 (c).

We find that both $\lambda_{\max}$ and $PR\lambda_{\max}$ have large values for periods containing the cryptomarket crashes and critical events. At the same time, their growth begins in the pre-crashes periods. Means, as well as the economic mass, they are quantum precursors of crashes and critical events phenomena.

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 systems 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 quantum 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.

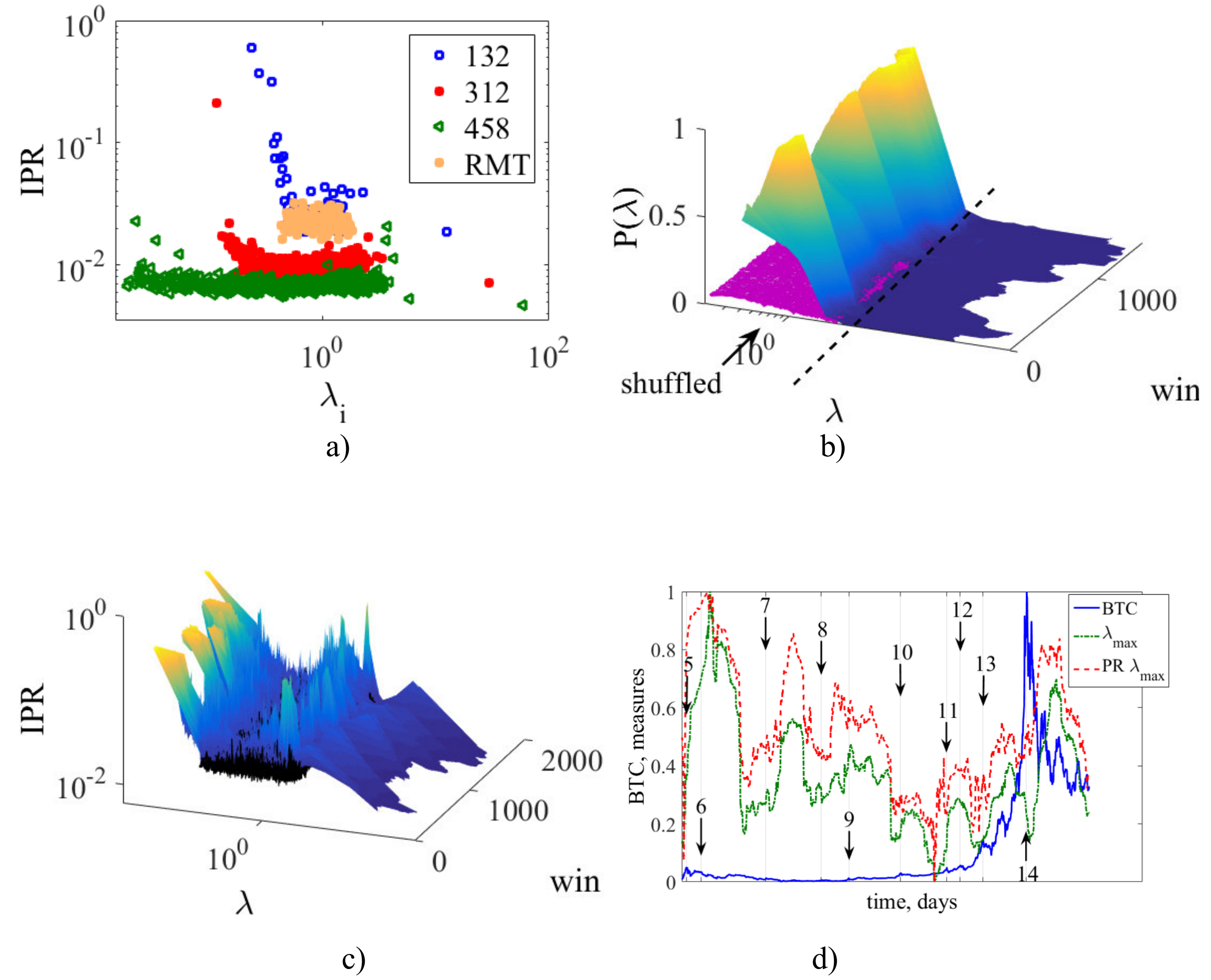


Fig. 5. Inverse participation ratio (a) and moving window dynamics of the eigenvalues distribution (b), IPR for the initial and mixed (or random) matrices (c). (d) quantum measures of complexity λ_{max} and its participation ratio. The numerics in the figure indicate the numbers of crashes and critical events in accordance with the table

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 quantum econophysics has a powerful toolkit of methods and models for creating effective indicators-precursors of crisis phenomena. In this paper, we have explored the possibility of using the Heisenberg uncertainty principle and random matrix theory to detect dynamical changes in a complex time series. We have shown that the economic mass m, and the largest eigenvalue λ_{max} may be effectively used to detect crisis phenomena for the cryptocurrencies time series. We have concluded though by emphasizing that the most attractive features of the m, λ_{max} and $PR\lambda_{max}$ namely its conceptual simplicity and computational efficiency make it an excellent candidate for a fast, robust, and useful screener and detector of unusual patterns in complex time series.

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ПЕРЕДВІСНИКИ КРАХІВ КРИПТОВАЛЮТ НА ОСНОВІ ПОКАЗНИКІВ КВАНТУМНОЇ ЕКОНОФІЗИКИ

Анотація. Вступ*. Нестабільність глобальних фінансових систем та наявність погано передбачуваних крахів на фінансових ринках свідчать про кризу методології моделювання, прогнозування та інтерпретації сучасних соціально-економічних реалій. Головною причиною цього є висока складність економічних систем, утворених з великої кількості взаємодіючих агентів, здатних генерувати нові властивості на рівні макроскопічної колективної поведінки, проявом якої є мимовільне утворення помітних часових, просторових чи функціональних структур. Одним з підходів до кількісного вимірювання складності є методи, що опираються на аналіз проявів складності системи І. Пригожина. Ключовою ідеєю тут є гіпотеза про зміну складності системи до та у період критичного явища. Ринок криптовалют – приклад економічних систем, складних для прогнозування. Це самоорганізована система, яку у більшості випадків можна розглядати або як складну мережу ринкових агентів, або як інтегрований вихідний сигнал такої мережі – часовий ряд, наприклад, ціни окремої криптовалюти. Дослідження коливань цін на криптовалюту ускладнюється завдяки наявності багатьох чинників – включаючи ринкові попит та пропозицію, обмінний курс долара США, стан фондового ринку, вплив злочинності, тіньовий ринок тощо, які вносять високий рівень шуму у дані. За рахунок цього ціни на криптовалюту демонструють такі складні важко передбачувані характеристики як волатильність, нелінійність та невизначеність.*

Метою статті *є розгляд деяких інформативних мір складності та адаптація їх для вивчення критичних та кризових явищ на ринку криптовалют.*

Проведення дослідження*. Для дослідження використано часовий ряд курсу Біткойна, взятого за період з 16.07.2010 р. по 08.12.2018 р., а також часові ряди курсів 1047 криптовалют, взятих за період з 31.12.2017 р. по 15.09.2018 р. На основі часового ряду Біткойна досліджувалась поведінка показника економічної маси до та під час критичного явища на крипторинку. Система криптовалют досліджувалась з використанням інструментів теорії випадкових матриць. Аналізувалась як безпосередньо сама матриця крос-кореляцій агентів економічної системи, так і її похідні, а саме – розподіл власних значень та власні вектори матриці крос-кореляцій.*

Результати та висновки*. Моніторинг та прогнозування можливих критичних змін на ринку криптовалюти мають першочергове значення. У статті досліджено можливість використання квантових мір складності для виявлення динамічних змін у складному часовому ряді. Показано, що застосовані заходи дійсно можуть бути ефективно використані для виявлення аномальних явищ для часових рядів криптовалют. На основі часового ряду Біткойна показано, що моніторинг та прогнозування можливих критичних змін криптовалют є першочерговим завдання аналізу. Досліджено можливість використання принципу невизначеності Гейзенберга та теорії випадкових матриць для виявлення динамічних змін у складному часовому ряді. Показано, що економічна маса та найбільше власне значення матриці крос-кореляцій можуть ефективно використовуватися для виявлення кризових явищ. Саме економічна маса завдяки концептуальній простоті поняття та обчислювальній ефективності є відмінним кандидатом для швидкого та надійного моніторингу незвичайної поведінки економічної системи.*

Ключові слова: *криптовалюта, біткойн, складна система, міри складності, аварії, критичні події, складні мережі, квантова еконофізика, принцип невизначеності Гейзенберга, теорія випадкової матриці, індикатор-попередник.*

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