Entropy Analysis of Crisis Phenomena for DJIA Index

Vladimir Soloviev[1], Andrii Bielinskyi[1], Viktoria Solovieva[2]

[1]Kryvyi Rih State Pedagogical University, 54, Gagarina Ave., Kryvyi Rih, 50086, Ukraine
[2]Kryvyi Rih Economic Institute of Kyiv National Economic University named after Vadym Hetman, 16, Medychna St., Kryvyi Rih, 50000, Ukraine
{vnsoloviev2016, krivogame, vikasolovieva2027}@gmail.com

Abstract. The Dow Jones Industrial Average (DJIA) index for the 125-year-old (since 1896) history has experienced many crises of different nature and, reflecting the dynamics of the world stock market, is an ideal model object for the study of quantitative indicators and precursors of crisis phenomena. In this paper, the classification and periodization of crisis events for the DJIA index have been carried out; crashes and critical events have been highlighted. Based on the modern paradigm of the theory of complexity, a spectrum of entropy indicators and precursors of crisis phenomena have been proposed. The entropy of a complex system is not only a measure of uncertainty (like Shannon's entropy) but also a measure of complexity (like the permutation and Tsallis entropy). The complexity of the system in a crisis changes significantly. This fact can be used as an indicator, and in the case of a proactive change as a precursor of a crisis. Complex systems also have the property of scale invariance, which can be taken into account by calculating the Multiscale entropy. The calculations were carried out within the framework of the sliding window algorithm with the subsequent comparison of the entropy measures of complexity with the dynamics of the DJIA index itself. It is shown that Shannon's entropy is an indicator, and the permutation and Tsallis entropy are the precursors of crisis phenomena to the same extent for both crashes and critical events.

Keywords: stock market, Dow Jones Industrial Average index, complex systems, measures of complexity, crash, critical event, permutation entropy, Shannon entropy, Tsallis entropy, multiscale entropy, indicators and precursors.

1 Introduction

For the last few decades, the behavior of the global financial system has attracted considerable attention. Wild fluctuations in stock prices lead to sudden trend switches in a number of stocks and continue to have a huge impact on the world economy causing the instability in it with regard to normal and natural disturbances [1]. Stock market prediction is a classic topic in both financial circles and academia. Extreme stock market fluctuations, e.g., the global stock market turmoils in September 2008, February 2018 damage financial markets and the global economy [2]. Thus we need a more effective way of predicting market fluctuations. Among the many predictive quantitative methods and models, Stanley et al. [3] distinguish such as autoregressive integrated moving average (ARIMA) models, artificial neural networks, support vector machine, and neuro-fuzzy based systems. Recent developments in artificial intelligence and the use of artificial neural networks have increased our success in nonlinear approximation. Previous studies indicate that “deep learning” (DL) solves nonlinear problems more efficiently than traditional methods [4, 5]. Irrespective of the level of complication or the presence of linear and nonlinear big data financial market factors, DL can extract abstract features and identify hidden relationships in financial markets without making econometric assumptions [5]. Traditional financial economic methods and other quantitative techniques cannot do this. Of particular interest are the combined models that include the best aspects of both classical econometric models and modern DL and complex systems models [6].

As for the models and mechanisms of stock market crashes, first of all, it should be noted the works of D. Sornette, which include both a historical overview of the causes of stock crashes [1, 7], the Log-Periodic Power Law Singularity model of financial bubbles [1, 8] and agent-based model [9].

It should be specially noted that we are setting ourselves the task of predicting neither future index values, nor possible trends. Our task is to highlight among the various manifestations of crisis phenomena such patterns that foreshadow in advance noticeable drops in the index value. This allows you to construct a precursor of the approaching crisis.

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. A similar idea has attracted considerable attention from the community of different branches of science in recent years [10, 11].

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 [12]. As simulation processes, the application of quantitative methods involves measurement procedures, where importance to complexity measures has been given. 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 phenomenon of complexity [13]. 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 financial market is a kind of complex systems with all kind of interactions [14]. Apart from many properties that they interact with other natural complex systems, they have a unique property – their building elements which called investors. In fact, they represent examples of complexity in action because many factors on financial markets and their evolution are dictated by the decision of crowds. Therefore, the financial markets have exceptionally strong ability to self-organize and their characteristics as nonlinearity and uncertainty remains a huge challenge.

The key idea behind our research is that the complexity of the system must change before crisis periods. This should signal the corresponding degree of complexity if they are able to quantify certain patterns of a complex system. A significant advantage of these measures is that they can be compared with the corresponding time series for monitoring and detecting critical changes of it. This opportunity allows us to use these quantitative measures of complexity in the diagnosis process and prediction of future changes.

The paper is structured as it follows. In Section 2 we describe how many articles and research papers were devoted to the topic of our research. Section 3 presents how we classified our data. Sections 4 and 5 demonstrate methods and results for Permutation, Shannon and Tsallis entropies. The market was analyzed in more detail using Multiscale entropy in Section 6. And finally, on the basis of the conducted research, we draw conclusions in Section 7.

2 Review of Previous Studies

Today Dow Jones Industrial Average index (DJIA) is most quoted financial barometer in the world and has become synonymous with the financial market in general. The *Industrial* portion of the name DJIA is largely historical, as many of the modern 30 components have little or nothing to do with traditional heavy industry. Since April 2, 2019, the DJIA includes 30 companies of the American stock market belonging to different sectors of the economy: industrial - 7 (23%), financial - 5 (17%), IT & Telecommunication – 6 (20%), Managed health care & Pharmaceuticals – 4 (13%), Retail, Food, Apparel and other – 8 (27%). In addition, the DJIA index has high pair-correlation coefficients with the most well-known country stock indexes. Due to these reasons, including to itself significant variety of stocks and having a confidence form many people, its dynamics plays an important role in the world economy.

There are a lot of articles and research papers that have been devoted to the DJIA index and its internal dynamics. For example, Charles with Darné [15] determined the events that caused large shocks volatility of the DJIA index over the period from 1928-2013, using a new semi-parametric test based on conditional heteroscedasticity models. They found that these large shocks can be associated with particular events (financial crashes, elections, wars, monetary policies, etc.) They showed that some shocks are not identified as extraordinary movements by the investors due to their occurring during high volatility episodes, especially the 1929-1934, 1937-1938 and 2007-2011 periods.

Also, there are different articles in which authors using entropy principles to detect aggregate fears and major crashes. Gençay and Gradojevic [16] developed a dynamic framework to identify fluctuations through the skewness premium of European options. Their methodology is based on measuring the distribution of a skewness premium through a q-Gaussian density and a maximum entropy principle. Their findings indicate that the October 19th, 1987 crash was predictable from the study of the skewness premium of deepest out-of-the-money options about two months prior to the crash. H. Danylchuk et al. [17] examined the entropy analysis of regional stock markets. Their paper proposed and empirically demonstrated the effectiveness of using such entropy as Sample entropy, Wavelet and Tsallis entropy as a measure of uncertainty and instability which dynamics can be used such as crisis prediction indicators. Authors of another paper [18] investigated the relationship between the information entropy of the distribution of intraday returns of intraday and daily measures of market risk. Using data on the EUR/JPY exchange rate, they found a negative relationship between entropy and intraday Value-at-Risk, and also between entropy and intraday Expected Shortfall. This relationship is then used to forecast daily Value-at-Risk, using the entropy of the distribution of intraday returns as a predictor. The research paper of Jun Lim [19] aims to study the efficiency of Permutation entropy in financial time series prediction and primarily focuses on the proposal, implementation and performance evaluation of a novel hash function to optimize the hashing of a large sequence of permutations based on a given financial data series.

In addition to scientific papers on such types of entropy, there are many works on Multiscale types of entropies. R. Gu in his research [20] introduced a new concept of singular value decomposition Multiscale entropy and studied its predictive power on the DJIA index. It was found that from the perspective of linearity, useful information and noise do not have the predictive power on the DJIA index. However, from the perspective of nonlinearity, the useful information has the predictive power on the index in the long-term (at least one year) period, and noise only has the predictive power on the index in the short-term (about one month) period. This means that both useful information and noise have predictive power on stock index, but their capacity of predicting (predictive term) is different, and these predictive powers are presented through nonlinear mechanism rather than the simple linear mechanism. Wang et al. [21] characterize market efficiency in foreign exchange markets by using the Multiscale approximate entropy to assess their randomness. They split 17 daily foreign markets rates from 1984 to 2011 into their periods by two global events: Southeast Asia currency crisis and American sub-prime crisis. The empirical results indicate that the developed markets are more efficient than emerging and that the financial crisis promotes the market efficiency in foreign exchange markets significantly, especially in emerging markets, like China, Hong Kong, Korea, and African market. Paweł Fiedor in cooperation with other researchers [22] extended some of their previous ideas and articles by using the Multiscale entropy analysis framework to enhance their understanding of the predictability of price formation process at various time scales. For their purpose, they estimated Shannon's entropy rate and also used the Maximum Entropy Production Principle as a more constructive framework. Their results indicate that price formation processes for stocks on Warsaw's market are significantly inefficient at very small scales, but these inefficiencies dissipate quickly and are relatively small at time scales over 5 price changes. Further, they showed that the predictability of stock price changes follows a fat-tailed distribution, and thus there exist some predictable price formation processes for some stocks. Strikingly, the Multiscale entropy analysis presented in their study shows that price formation processes exhibit a completely opposite information-theoretic characteristic to white noise, calling into question methods in finance based on Brownian motion or Lévy processes.

This briefly described list of studies shows that the researching of the dynamics of stock markets, the prevention of crisis phenomena on them and the creation of new methods and instruments for these purposes are relevant.

In our previous research papers, we used measures of complexity to prevent crisis states on the cryptocurrency market [23, 24]. The spectrum of entropy measures for the stock market, on the example of the DJIA index, is used in this paper.

3 Classification of Data

Financial indices are the main indicators of the work of the stock markets. The DJIA index is the most well-known “blue-chips” stock index. For understanding of the falls that occurred on it, our classification and constructing our indicators, we divided its time series into two parts during the periods from 2 January 1920 to 3 January 1983 and from 4 January 1983 to 18 March 2019 of flexible daily values of the DJIA index.

During the research, crises were separated into crashes and critical events, and it was established that:

- Crashes are short, time-localized drops, with the strong losing of price each day.
- Critical events are those falls that, during their existence, have not had such serious changes in price as crashes.

Obviously, during DJIA index existence, many crashes and critical events shook it. Relying on historical data and normalized returns, where returns are calculated as $g(t) = \ln X(t+\Delta t) - \ln X(t) \cong [X(t+\Delta t) - X(t)]/X(t)$, we emphasize that almost 20 crashes and critical events took place, whose falling we identify and predict by our indicators. More detail information is presented on the Sheet below.

Table 1. List of DJIA Major Historical Corrections since 1929.

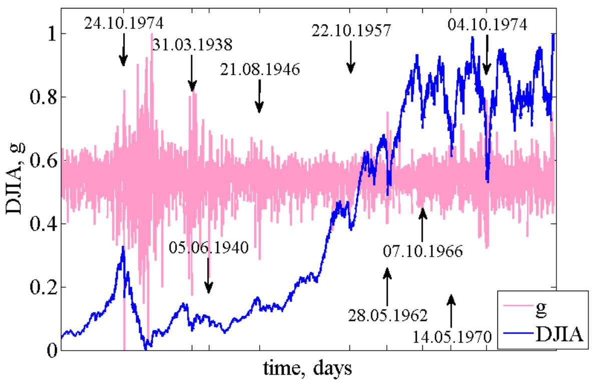
№	Interval	Days in correc-tion	DJIA High Price	DJIA Low Price	Decline, %
1	03.09.1929-29.10.1929	41	381,17	230,07	39,64
2	01.03.1938-31.03.1938	23	130,47	98,95	24,15
3	08.04.1940-05.06.1940	42	151,29	113,25	25,10
4	21.08.1946-10.09.1946	14	200,00	167,30	16,35
5	30.07.1957-22.10.1957	60	508,93	419,79	17,51
6	19.03.1962-28.05.1962	50	720,38	576,93	19,91
7	18.07.1966-07.10.1966	59	888,41	774,32	12,84
8	09.04.1970-26.05.1970	34	792,50	631,16	20,35
9	24.10.1974-04.10.1974	52	805,77	584,56	27,45
10	02.10.1987-19.10.1987	12	2640,99	1738,74	34,16
11	17.07.1990-23.08.1990	28	2999,75	2483,42	17,21
12	01.10.1997-21.10.1997	15	8178,31	7161,14	12,43
13	17.08.1998-31.08.1998	11	8533,65	7640,27	18,44
14	14.08.2002-01.10.2002	34	9053,64	7286,27	19,52
15	16.10.2008-15.12.2008	42	11715,18	8175,77	30,21
16	09.08.2011-22.09.2011	32	12190,01	10733,83	11,94
17	18.08.2015-25.08.2015	6	17511,34	15666,44	10,53
18	29.12.2015-20.01.2016	16	17720,98	15766,74	11,02
19	03.12.2018-24.12.2018	15	25826,42	21792,19	15,62

According to our classification events with the number (1, 10, 13, 15, 19) are crashes, all the rest are critical events. Further on, we will consider those entropy indicators that, from the point of view of identification and prevention of crisis phenomena are the most informative. Analysis of the whole set of such indicators allowed us to identify 3 of them: Permutation, Shannon and Tsallis entropies.

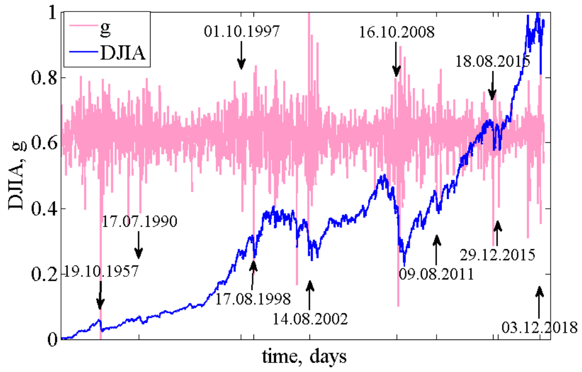
Results were obtained within the framework of the algorithm of a moving window. For this purpose, the part of the time series (window), for which there were calculated measures of complexity, was selected, then, the window was displaced along the time series in a five-day increment and the procedure repeated until all the studied series had exhausted. Worth to note that if the length of the time window is too wide, several crises may entire it and our indicators will not reflect future entire changes correctly. Also, the window cannot be too narrow because the measure of complexity fluctuates noticeably and requires smoothing. During the experiments, we found that the window 500 represents the optimal results.

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 stock index. If the constructed measure of complexity behaves in a definite way for all periods of crashes, for example, decreases or increases during the pre-critical period, then it can serve as an indicator or precursor of such a crashes phenomenon.

In the Figure 1 two output DJIA time series, normalized returns $g(t)$ with emphasized crisis states are presented.



a)



b)

Fig. 1. The standardized dynamics and returns $g(t)$ of DJIA daily values for the first (a) and the second (b) periods. The arrows indicate the corresponding crash or critical event.

As we can see from Figure 1, for most crashes and critical events, normalized profitability $g(t)$ increases considerably in some cases. This behavior signals about abnormal phenomena in the market, and deviation from the normal law of distribution. Such characteristic can serve as indicator of critical and crash phenomena.

4 Permutation Entropy

Permutation entropy (PEn) is a measure from the chaos theory, proposed by Bandt and Pompe [25], which is characterized by its conceptual simplicity and computational speed. The idea of PEn is based on usual Shannon entropy [26], but it uses permutation patterns-ordinal relations between values of the system. These patterns consider the order among times series and relative amplitude of values in each vector instead of individual values. In this way, if compared with other measures of complexity, this approach has many advantages over the others as robustness to noise and invariance to nonlinear monotonous transformations [27]. The PEn can be described as follows.

Let's consider time series $S(t)=\{x_k \mid k=1,\dots,N\}$. For a given time series can be constructed embedding vector:

$$S_m \to (x_{m-(D-1)L}, x_{m-(D-2)L}, \dots, x_{m-L}, x_m),$$

where D is the length of embedding dimension, and L is the time delay. For constructing ordinal patterns each element of the vector can be defined by order

$$x_{m-j_0 L} \ge x_{m-j_1 L} \ge \dots \ge x_{m-j_{D-2} L} \ge x_{m-j_{D-1} L}.$$

Therefore, for the vector S_m there will be $D!$ possible permutations $\pi = (j_0, j_1, \dots, j_{D-1})$. Then, we obtain the probability for each π and construct the ordinal pattern probability distribution $P = \{p_i(\pi_i), i = 1, \dots, D!\}$ required for the entropy estimation. The Permutation entropy (denoted by $S[P]$) of the time series $S(t)$ is defined as:

$$S[P] = -\sum_{i=1}^{D!} p(\pi_i) \ln p(\pi_i) .$$

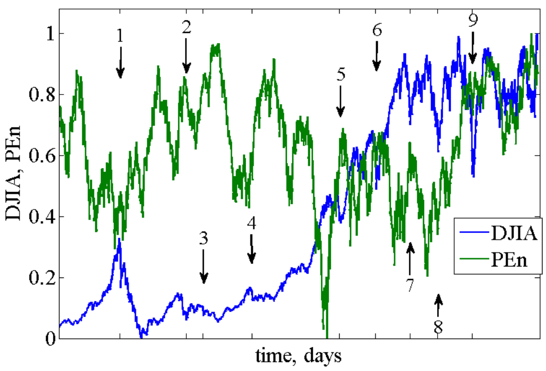
To take more convenient values, we normalize permutation entropy S associated with probability distribution P:

$$E_s[P] = \frac{S[P]}{S_{\max}},$$

where $S_{\max} = \ln D!$, and normalized permutation has a range $0 \le E_s[P] \le 1$.

The PEn is not restricted to the time series that is representative of low dimensional dynamical systems. The embedding length D is paramount of importance because it determines $D!$ possible states for the appropriate probability distribution. With small values such as 1 or 2, parameter D will not work because there are only few distinct states. Furthermore, for obtaining reliable statistics and better detecting the dynamic structure of data, $D!$ should be relevant to the length of the time series or less [20]. We discovered that $D = 5, 6$, or 7 indicate better results. Therefore, the value of $H_s[P]$ gives us to understand rather we have predictable and regular time series or absolutely randomize process.

Figure 2 shows the PEn calculation results both for first (a) and second (b) periods of the DJIA index time series (the window length is 500 days, the offset is 5 days). Arrows indicate crashes and critical events according to their number in the table.



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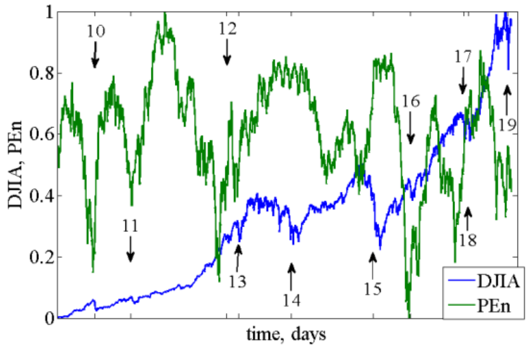


b)

Fig. 2. The dynamics of Permutation entropy for first (a) and second (b) periods of the DJIA index time series.

As we can see from the figures above, Permutation entropy decreases for both crashes and critical events, signaling the approaching of a special state.

5 Indicators of crisis states based on Shannon and Tsallis entropies

For a given discrete probability distribution $P = \{p_i, i = 1, \dots, M\}$, Shannon entropy (ShEn) is defined as:

$$S[P] = -\sum_{i=1}^{M} p_i \ln p_i .$$

For any scale $c \neq 0$, ShEn is defined as:

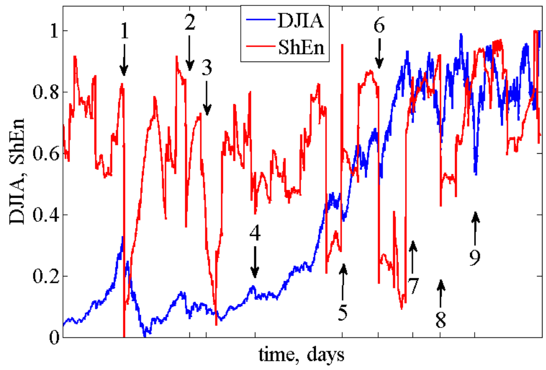
$$S_c = \left[\sum_{i=1}^{M} p_i (\ln p_i^{-1})^c \right]^{1/c} .$$

where p_i stands for the occurrence probability of one event. For scale $c = 0$, the $c - th$ order of ShEn is defined as:

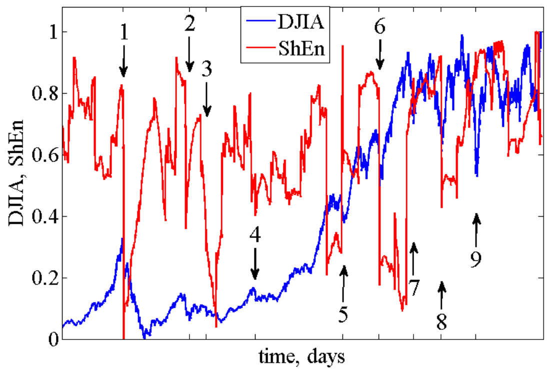
$$S_c = \prod_{i=1}^{M} e^{p_i} (\ln p_i^{-1}).$$

These equations are jointly called as the generalized ShEn. When $c = 1$, generalized entropy transforms into the standard Shannon entropy.

Figure 3 demonstrates the dynamics of DJIA index and calculated ShEn for them with parameters: the length of window is 500 days and window offset is 5 days.



a)



b)

Fig. 3. Dynamics of Shannon entropy and the DJIA index for first (a) and second (b) periods.

It can be noticed that in crashes or critical periods ShEn decreases, indicating abnormal phenomena that took place in the stock market. With the lower value of entropy, we have less complexity in the system (crisis period), and when the value of entropy becomes higher, the system becomes more chaotic and randomized. It's worth considering that this indicator responds significantly to those events that have had rapidly price loss in a short period of time.

Tsallis [28] introduced a new concept that allows describe non-extensive (non-additive) systems with the entropic index q which is the measure of non-additivity such as:

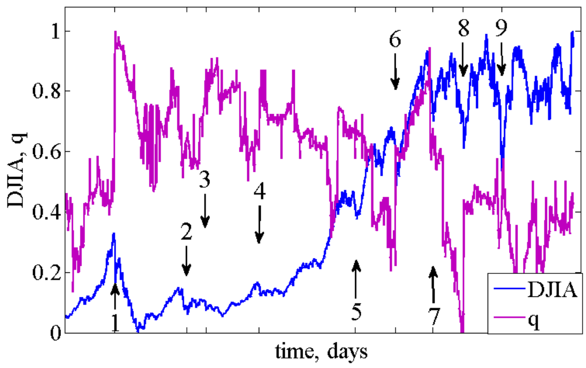
$$S(A+B)=S(A)+S(B)-(1-q)\cdot S(A)\cdot S(B).$$

He took the standard Shannon's entropy expression and instead of the logarithmic one, he introduced power function $\ln(x) \Rightarrow \ln_q(x) \Rightarrow (x^{1-q}-1)/(1-q)$. In the limit as $q \to 1$, $\ln_q(x)$ turns into real logarithm. For the entropic index q new entropy is defined as:

$$S_q = -\sum_i (p_i^q \ln_q(p_i)) = (1-\sum p_i^q)/(q-1),$$

where new q-entropy can give description of systems with "long memory" in which interacts not only with nearest neighbors, but with entire systems or with some of its parts. With the entropic indicator q it is possible to determine different characteristics of complex systems. When the entropic index $q<1$, it means that in system dominates unusual anomalous phenomena. With the entropic index $q>1$ determined recurring phenomena in the system. In the case, when the entropic index $q \to 1$, Tsallis entropy converges to the standard ShEn. The main consequence of such substitution is that entropy with the entropic index q is an already non-extensive function.

In Figure 4 we present comparative dynamics of the DJIA index with corresponding value of q which is considered to be an indicator of crisis states. The results were obtained for window of length 1000 days and window offset 5 days.



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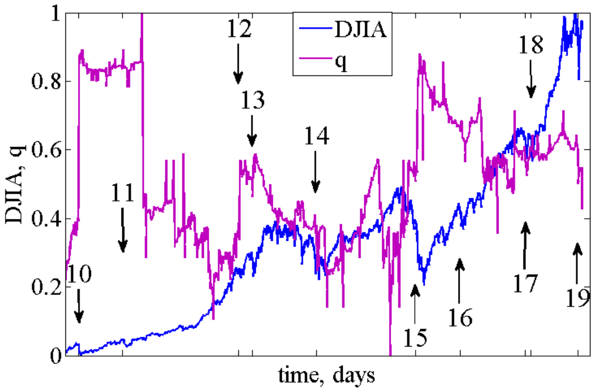


b)

Fig. 4. Comparative dynamics of DJIA index time series with corresponding value of q coefficient for first (a) and second (b) periods.

For Figure 4 in most crashes and critical events, the entropic index q rapidly and asymmetrically growths and indicates the increasing in complexity of the system at that time. It is worth considering that with the window of less width and step, we would have taken results with higher accuracy.

As a result, Shannon's entropy is an indicator, and the parameter q is a precursor of crisis phenomena.

6 Multiscale entropy

One of the properties of complex systems is manifested in their scale invariance: a complex system behaves universally, regardless of the scale. This feature is found in the quantitative description of entropy, which is known as Multiscale entropy (MSE). The algorithm of MSE was developed by Costa [29] to quantify the complexity of time series for a range of scales (see Figure 5).

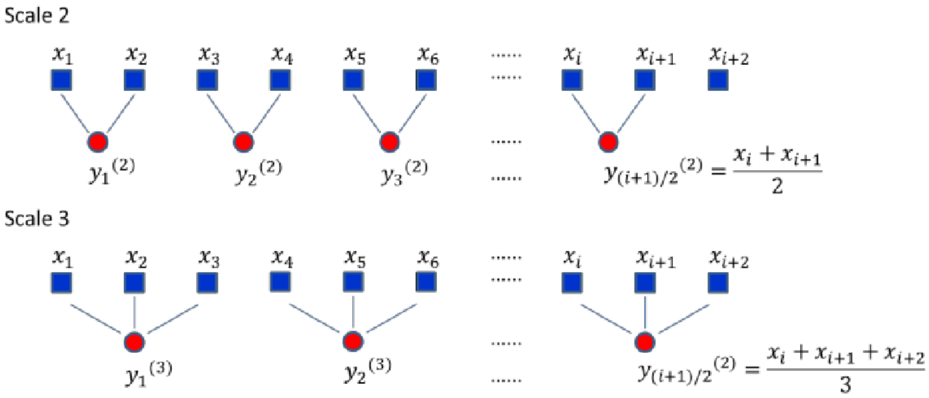


Fig. 5. Schematic illustration of the coarse-graining for scales 2 and 3.

The MSE method includes two sequentially executed procedures:

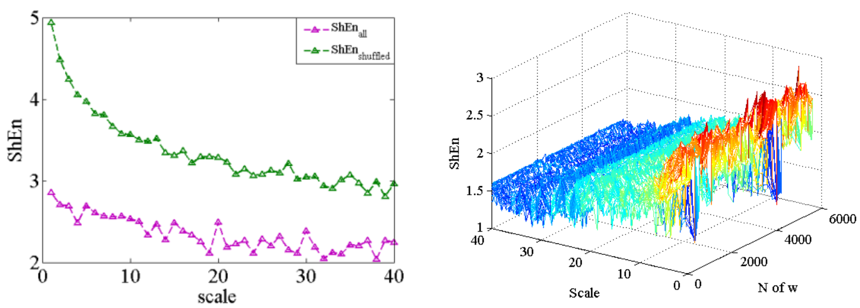
(1). The process of coarse-graining of the initial time series. To obtain coarse-grained time series at a scale factor of τ, time series divides by the non-overlapping windows of the length τ as shown in Figure 5, and the size of which increases with the transition from scale to scale. Then, the values inside each part of the time series are averaged. In other words, each element $y_j^{(\tau)}$ for the coarse-grained times series can be estimated according to the following equation:

$$y_j^{\tau} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, 1 \le j \le N/\tau.$$

The length for each coarse-grained time series depends on the length of the window and equals to N/τ. For a scale of 1, the coarse-grained time series identical to the original one.

(2). The computation of the corresponding measure of entropy as a measure of complexity for each coarse-grained time series. This measure then plotted as the function of the scale factor τ (according to our case, we estimate Shannon entropy).

As a result, in the Figure 6 we can see MSE calculated for the entire DJIA index time series



a) b)

Fig. 6. The map of multiscaling components for estimated Shannon entropy for the entire DJIA index time series.

Figure 6 (a) shows the Multiscale Shannon entropy calculated for the entire output and shuffled DJIA time series. The fact that the shuffled time series is more complex suggests that the Shannon entropy is a measure of chaotic rather than complexity. Figure 6 (b) is a three-dimensional representation of Shannon entropy calculated with a window length of 1000 days, a window offset of 5 days and scale factor of 40. It is seen that at small scales, the dynamics of MSE coincide with Figure 3 and even at the presented scales, it does not tend to zero.

7 Conclusions

Anomalous fluctuations of the daily values of the Dow Jones Industrial Average index for the period from 2 January 1920 to 18 March 2019 have been analyzed; 5 crashes (short, time-localized drops) and 14 critical events (price changes that are noticeable but occurring over a longer period of time) have been identified. The hypothesis on the correlation of complexity measures and crisis phenomena, proposed on the basis of the theory of complex systems, has been tested using the example of entropy complexity measures. The entropy (including multiscale versions) of Shannon, Tsallis, and permutations are calculated within the framework of the moving window algorithm from a set of entropy indicators. The change in the absolute values of the entropy indices in the period of the crash and critical events indicates a change in the complexity of the system, which makes it possible to treat them as informational measures of complexity. Comparison of the entropy characteristics with the values of the DJIA index opens up the possibility of indicating or even early warning of crisis phenomena. In the case of Shannon's entropy, the complexity of the system experiences a race itself at the moment of crisis and is its indicator. The entropy of Tsallis and permutations react to crisis phenomena with some anticipation, which makes it possible to use them as precursors of crises.

Thus, the developed methodology for constructing indicators and precursors of crisis phenomena does not use cumbersome, costly and still debatable methods for predicting price fluctuations and their trends, carry out early diagnostics of crisis phenomena and take preventive measures anticipating significant financial losses.

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