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SYSTEMS ANALYSIS MODELS IN THE ECONOMIC PROCESSES MANAGEMENT

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МОДЕЛИ СИСТЕМНОГО АНАЛИЗА В УПРАВЛЕНИИ ЭКОНОМИЧЕСКИМИ ПРОЦЕССАМИ

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The monograph examines models of systems analysis in the management of economic processes at the macro, meso and micro levels. Models of neural networks for solving the problems of dynamic clustering of economic systems by the level of resistance to the impact of "shocks", machine learning models for managing the safety of socio-economic systems, models for assessing the level of social tension, models for the development of complex socio-economic systems, models for structural analysis of the development of territorial formations have been developed. Special attention is paid to systemic modeling of financial processes and organizations' management. The paper proposes models of financial security management, models for early recognition of crises, models for making optimal investment decisions, considers the possibilities of using methods and models of data mining in the banking sector, proposes models for forming a marketing mix of companies based on DATA SCIENCE technologies, models for monitoring personnel resistance to organizational changes, models of system analysis in the project activities of organizations management .

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В монографии рассматриваются модели системного анализа в управлении экономическими процессами на макро-, мезо- и микроуровне. Разработаны модели нейронных сетей для решения задач динамической кластеризации экономических систем по уровню устойчивости к воздействию «шоков», модели машинного обучения для управления безопасностью социально-экономических систем, модели оценки уровня социальной напряженности, модели развития сложных социально-экономических систем, модели структурного анализа развития территориальных образований. Особое внимание уделено системному моделированию финансовых процессов и управлению организациями. В работе предложены модели управления финансовой безопасностью, модели раннего распознавания кризисов, модели принятия оптимальных инвестиционных решений, рассмотрены возможности использования методов и моделей интеллектуального анализа данных в банковской сфере, предложены модели формирования маркетинг-микса компаний на базе DATA SCIENCE технологий, модели мониторинга сопротивления персонала организационным изменениям, модели системного анализа в управлении проектной деятельностью организаций.

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СОДЕРЖАНИЕ

2.4. Permutation based complexity measures and crashes

Introduction

The achievements of recent years in the field of quantitative description of financial and economic systems are associated with the formation and development of tools for the theory of complex systems [1] and its pragmatic branch – econophysics [2]. The emergence of a large number of measures of complexity made it possible to more effectively manage complex systems in conditions far from equilibrium, predict and prevent critical and crisis phenomena [14].

Among the many complexity measures that have passed the test of time, permutation based measures occupy an important place. Thus, introduced in 2002 by Bandt and Pompe permutation entropy [3] has become a theoretically transparent and practically effective tool for quantifying the complexity of systems of various natures [4]. Introduced relatively recently, the permutation measure of irreversibility of the time series [5] has expanded the range of permutation measures of complexity.

The purpose of this work is to study the sensitivity of permutation measures of complexity to crisis phenomena in markets that are different in structure and dynamics; stock, cryptocurrency and oil.

The use of the Dow Jones index in calculating the permutation entropy [6-9] was aimed at:

- to identify the difference in the behavior of the developed US market with the emerging market of China [6];

- analysis of the frequency of allowed and prohibited patterns for the index since 1900 [7];

- study of the permutation entropy dynamics of during crises periods [8, 9].

As for the crypto market, then authors [10-13] employed permutation entropy with a rolling window approach to test for the market efficiency, clustering patterns Bitcoin prices, forecasting Bitcoin’s daily value at risk. In a series of our works [14, 15], permutation entropy is used to construct indicators-precursors of crises in the crypto market.

There are relatively few studies on the permutation properties of the oil market [4, 16, 17]. It should be noted one of the first works [16], in which the authors compared the dynamics of permutation entropy with fluctuations of daily prices of crude oil WTI for the time period 1983-2015. They also showed how several events occurred contemporary to changes in the informational efficiency, providing evidence of some influence of main economic and political milestones in the dynamics of the crude oil market. In our recent work [17], the possibilities of permutation entropy in predicting crisis phenomena in the oil market are compared with the possibilities of other measures of complexity.

Permutation entropy (PEn)

PEn is characterized by its simplicity, computational speed that does not require some prior knowledge about the system, strongly describes nonlinear chaotic regimes. Also, it is characterized by its robustness to noise and invariance to nonlinear monotonous transformations. The combination of entropy and symbolic dynamics turned out to be fruitful for analyzing the disorder for the time series of any nature without losing their temporal information. According to this method, we need to consider "ordinal patterns" that consider the order among time series and relative amplitude of values instead of individual values. For evaluating PEn, at first, we need to consider a time series $\{x_i \mid i = 1, \ldots, N\}$ which can be revealed in d_E - dimensional vector

$$\vec{X}(i) = [x_i, x_{i+\tau}, \ldots, x_{i+(d_E-1)\tau}], \qquad \text{for} \quad i = 1, 2, \ldots, N-(d_E-1)\tau,$$

where d_E is the size of each embedded vector and τ is an embedding delay between each vector.

After it, we consider $d_E!$ permutation patterns $\pi = (k_0, k_1, \ldots, k_{d_E-1})$ of symbols $(0, 1, \ldots, d_E - 1)$ if the following condition for each $\vec{X}(i)$ is satisfied:

$$x_{i+k_0\tau} \le x_{i+k_1\tau} \le \ldots \le x_{i+k_{d_E-1}\tau}.$$

We will use ordinal pattern probability distribution as a basis for entropy estimation. Further, let us denote $f(\pi_l)$ as the frequency of occurrence of the pattern π_l. Then, the probability of occurrence of a specific pattern can be defined as

$$p(\pi_l) = \frac{f(\pi_l)}{N-(d_E-1)\tau}.$$

Then, regarding the ordinal pattern probability distribution $\mathrm{P} = \{p(\pi_l) \mid l = 1, \ldots, d_E!\}$, the permutation entropy of the corresponding time series can be defined following such equation:

$$S[\mathrm{P}] = -\sum_{l=1}^{d_E!} p(\pi_l)\log p(\pi_l).$$

If we need to compare time series with the described measure, we can normalize $S[\mathrm{P}]$:

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

where $S_{\max} = \ln d_E!$ is the highest value of PEn and $0 \le E_s[\mathrm{P}] \le 1$. There are enormous number of studies which imply that PEn values close to 1 suggest the presence of stochastic (random) processes; on the other hand, values close to 1 say about some deterministic patterns in the generating dynamics.

The first tusk that scientist solve applying PEn is the choice of appropriate set of parameters $d_E!$ and τ. As $d_E!$ defines the number of possible states that the embedded fragments can be in. Following Bandt and Pompe's recommendation [3], it is common to choose the values of d_E that satisfy the condition $d_E! << N$ for the appropriate probability distribution. For small values, such as $d_E = 2$, procedure may not be accurate enough, since there are only few particular states — $\pi_1 = \{0, 1\}$ and $\pi_2 = \{1, 0\}$. We will define the best set of parameters empirically.

Permutation based time irreversibility measure

We can define a time series as a reversible when there is an abundance of invariance of its statistical properties after operation of reversibility. Thus, for a given time series $\vec{X} = \{x_i \mid i = 1, \dots, N\}$, its time reversed version $\vec{X}^{t.r.} = \{x_i \mid i = N, \dots, 1\}$ is said to be reversible if for a mapping function $f(\cdot)$, $f(\vec{X}) \approx f(\vec{X}^{t.r.})$. Processes that are characterized as nonlinear, non-extensive, non-Gaussian, and with the presence of memory can be classified as irreversible. Assessing irreversibility of a system is equivalent to its predictability. Thus, procedure for obtaining ordinal patterns from permutation entropy approach will see to be reasonable in our case.

First of all, let is give an example of the procedure for calculating the necessary indicator of irreversibility. According to mentioned steps, we will construct embedded matrix of overlapping vectors with $d_E = 3$ and $\tau = 1$ for the fragment of West Texas Intermediate (WTI) crude oil price for period 14.07.2008-26.07.2008 (https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm):

$$\vec{X}^{d} = \{145.16, 138.68, 134.63, 129.43, 128.94, 131.43, 127.25\}$$

and

$$\vec{X}^{t.r.} = \{127.25, 131.43, 128.94, 129.43, 134.63, 138.68, 145.16\}.$$

Then, our embedded data can be presented in the following form:

$$\vec{X}^{d}(d_E, \tau) = \begin{bmatrix} 145.16 & 138.68 & 134.63 & 129.43 & 128.94 \\ 138.68 & 134.63 & 129.43 & 128.94 & 131.43 \\ 134.63 & 129.43 & 128.94 & 131.43 & 127.25 \end{bmatrix}$$

and

$$\vec{X}^{t.r.}(d_E, \tau) = \begin{bmatrix} 127.25 & 131.43 & 128.94 & 129.43 & 134.63 \\ 131.43 & 128.94 & 129.43 & 134.63 & 138.68 \\ 128.94 & 129.43 & 134.63 & 138.68 & 145.16 \end{bmatrix}$$

After it, our time-delayed vectors are mapped to permutations or ordinal patterns of the same size. Our example consists 3! = 6 different ordinal patterns.

These patterns can be composed in such a way that a time-reversible version of the same pattern will be paired with it:

$$\{0,1,2\} \overset{t.r}{\leftrightarrow} \{2,1,0\}$$

$$\{1,0,2\} \overset{t.r}{\leftrightarrow} \{2,0,1\}$$

$$\{1,2,0\} \overset{t.r}{\leftrightarrow} \{0,2,1\}$$

with $\overset{t.r.}{\leftrightarrow}$ representing a time reversal transformation.

Thus, we map our time delayed matrices to ordinal matrices:

$$\vec{\mathrm{X}}^{d}(d_E,\tau) = \begin{bmatrix} 2 & 2 & 2 & 1 & 1 \\ 1 & 1 & 1 & 0 & 2 \\ 0 & 0 & 0 & 2 & 0 \end{bmatrix} \quad \text{and} \quad \vec{\mathrm{X}}^{t.r.}(d_E,\tau) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 2 & 2 & 1 & 1 & 1 \\ 1 & 0 & 2 & 2 & 2 \end{bmatrix}.$$

According to our directed ordinal matrix, frequently we can observe pattern with two consecutive decreasing values, i.e., $\pi^d = \{2,1,0\}$; as this pattern does not appear in time reversed ordinal matrix, we can be certain about the time directionality of out time series. An opposite pattern $\pi^{t.r.} = \{0,1,2\}$ appears with the same frequency, which is time-reversed equivalent of our directed version. Thus, we can conclude out time reversibility of our time series, and opposite conclusions would be drawn for an irreversible version. This idea is a basis for the measure described below.

The irreversibility magnitude can be quantified by comparing the probability distributions of the patterns appearing in the original and time-reversed series through the Kullback-Leibler divergence [5, 18]. Following the example above, we construct the probability distribution for directed and reversed versions:

$$P^d = [\, p_{\{0,1,2\}} = 0;\ p_{\{2,1,0\}} = 0.6;\ p_{\{1,0,2\}} = 0.2;\ p_{\{2,0,1\}} = 0;\ p_{\{1,2,0\}} = 0.2;\ p_{\{0,2,1\}} = 0]$$

and

$$P^r = [\, p_{\{2,1,0\}} = 0;\ p_{\{0,1,2\}} = 0.6;\ p_{\{2,0,1\}} = 0;\ p_{\{1,0,2\}} = 0;\ p_{\{0,2,1\}} = 0.2;\ p_{\{1,2,0\}} = 0.2] \ .$$

The difference between two distributions then can be estimated through the following formula:

$$D_{KL} = \sum_{i=1}^{d_E!} P^d(i) \log \frac{P^d(i)+\varepsilon}{P^r(i)+\varepsilon},$$

where $\varepsilon << \min P^d$ and $\varepsilon << \min P^r$, since the argument of the logarithm can be $p_{\{1,0,2\}} / p_{\{2,0,1\}} = 0.2/0$.

Consequently, if $D_{KL} \approx 0$, the probability distributions of directed and time-reversed series should be approximately the same, and time series in this case is presented to be reversible. On the other hand, as $D_{KL} \to \infty$, dynamics of the system becomes more irreversible.

Empirical results for financial time series

Nowadays WTI crude oil, Bitcoin, and DJIA are presented to be one of the most influential assets, having a significant impact on the world economy. In our previous articles we have advanced into action and set the tasks (1) to make an appropriate classification of such events that are predictable and not predicta-ble and (2) to construct such indicators that will identify in advance crashes and critical events in order to allow investors and ordinary users to work in these markets. Our studies present that their price behavior is regime-switching. Such switching reveals in high risk (completely random) and low risk (deterministic) environments. Some of those events are much more predictable, less efficient, and exhibit corresponding complexity patterns that can serve as indicators of further falling.

This work focuses only on the most influential crisis events of WTI and DJIA, while in the Bitcoin market, all the crises discussed in previous works were selected and supplemented. The data we use here for our analysis are the daily closing prices of

- the crude oil price over the period from 2 January 1986 to 23 March 2021;
- the DJIA price for the period from 4 January 1983 to 23 March 2021;
- BTC time series that was divided into two periods: from 1 January 2011 to 31 August 2016 and from 1 September 2016 to 23 March 2021.

During these periods, markets have experienced varying degrees of volatility.

Calculations were carried out within the framework of the algorithm of a moving window. For this purpose, in each time window (frame) there was selected a part of a time series for which we calculated the measures of complexity (irreversibility). Then the window was displaced along with the time series in a predefined value, and the procedure repeated until all the studied series had exhausted. Further, comparing the dynamics of the actual time series and the corresponding measures, we can judge the characteristic changes in the dynamics of the behavior of complexity with changes in the system. If these measures behave in a definite way, example, increase or decrease during (pre-) crisis period, then it can serve as a measure of complexity (irreversibility) for a studying system.

Each measure was calculated regarding normalized returns, were returns can be calculated following the equation below:

$$G(t) = \ln x(t+\Delta t) - \ln x(t) \cong [x(t+\Delta t) - x(t)] / x(t).$$

Normalized returns can be found with the following formula:

$$g(t) \cong [G(t) - \langle G \rangle] / \sigma,$$

where σ is the standard deviation of G, Δt is the time lag between prices (in our case $\Delta t = 1$), and $\langle \ldots \rangle$ is the average over the time period under study.

Figures below present a comparative dynamics of studied financial systems and corresponding measures.

Comparison of the results for different window sizes shows that an increase in the window size leads to poor resolvability of crisis phenomena close in time. Therefore, in the future, in particular, in the case of the oil market, we chose a window of 250 days. For the more volatile cryptocurrency market, the optimal window was 100 days.

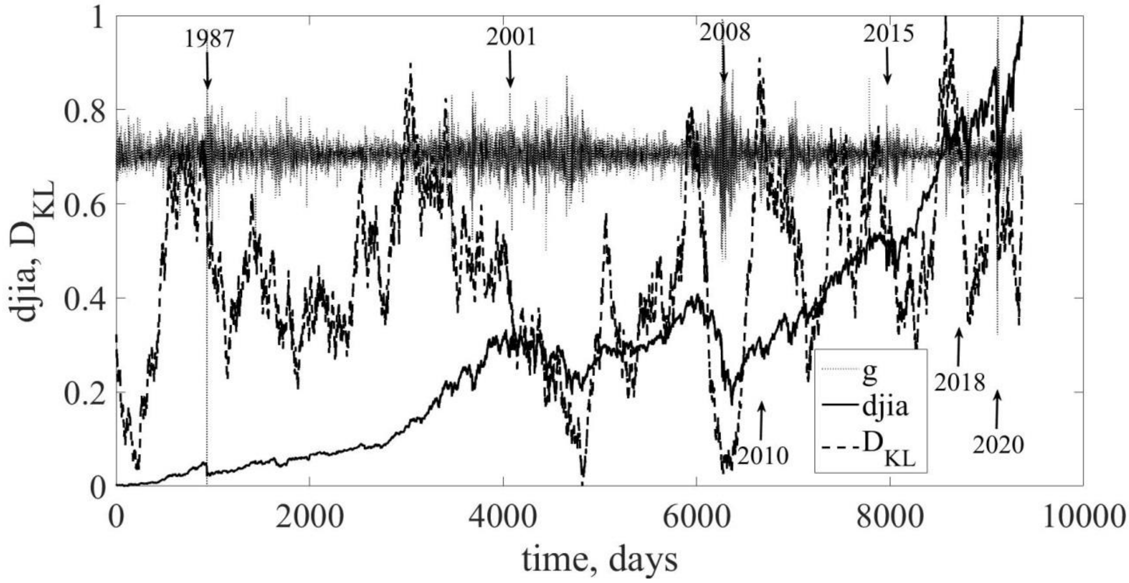


Fig. 1. Comparative dynamics of DJIA index along with its normalized returns g and D_{KL} calculated for rolling window of 250 days and step size of 1 day

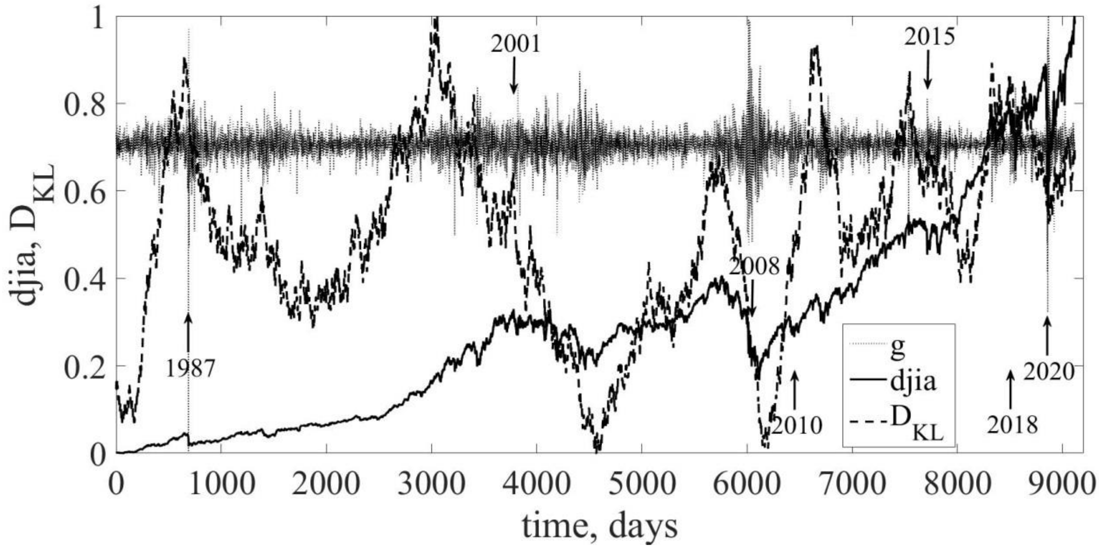


Fig. 2. Comparative dynamics of DJIA index along with its normalized returns g and D_{KL} calculated for rolling window of 500 days and step size of 1 day

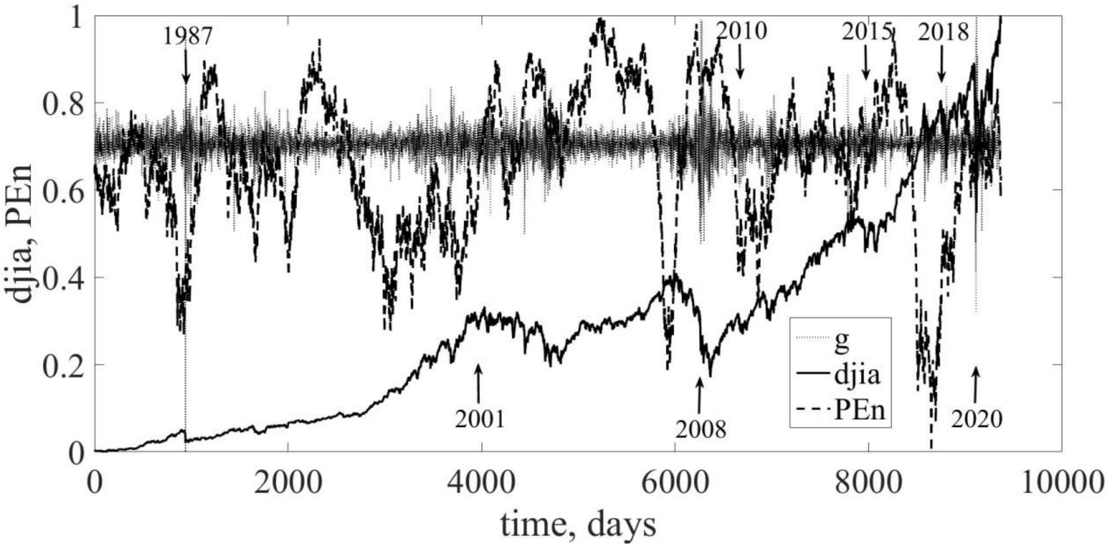


Fig. 3. Comparative dynamics of DJIA index along with its normalized returns g and PEn calculated with rolling window of 250 days and step size of 1 day

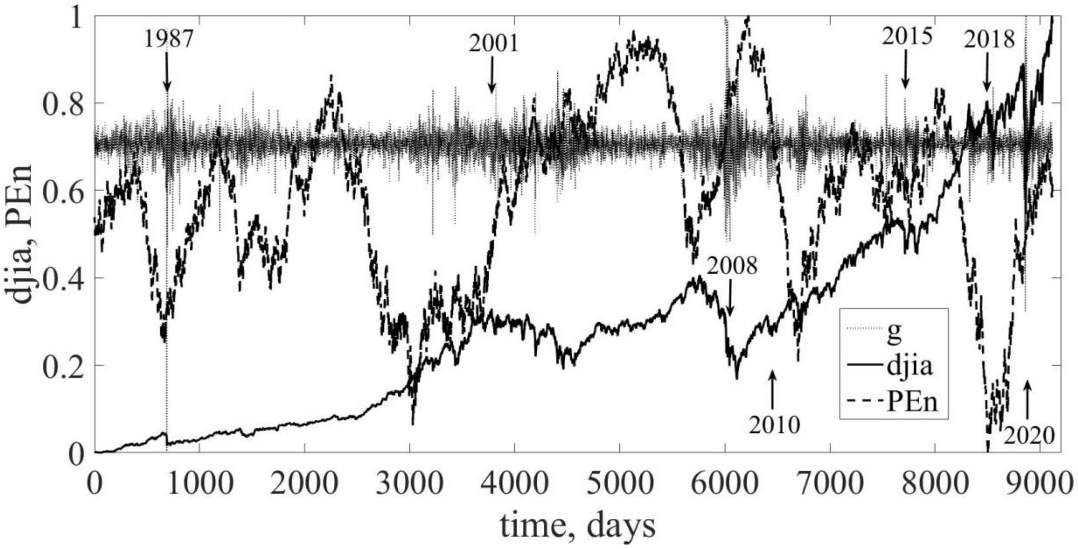
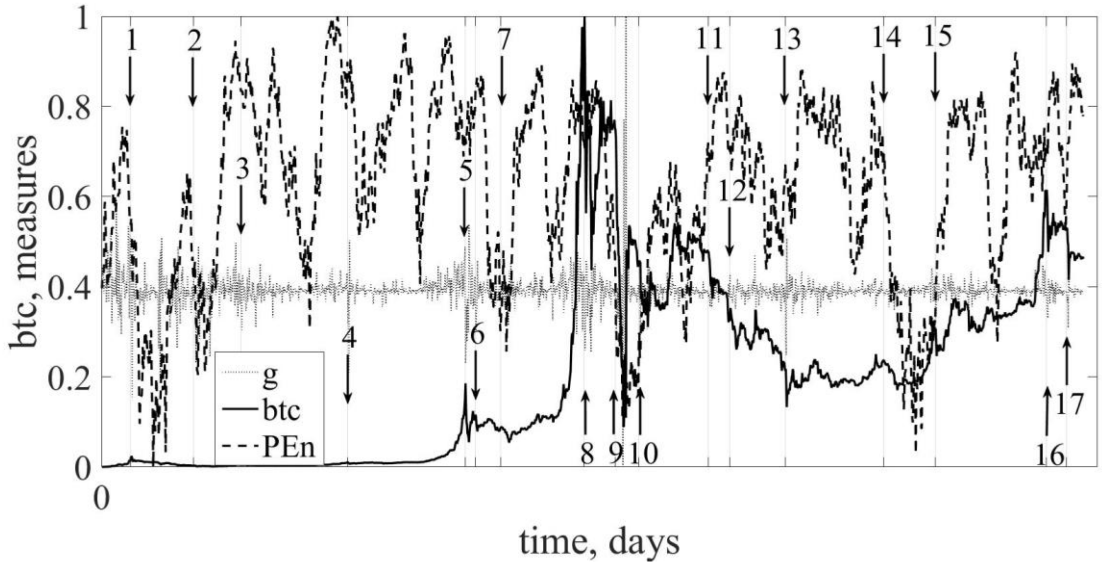
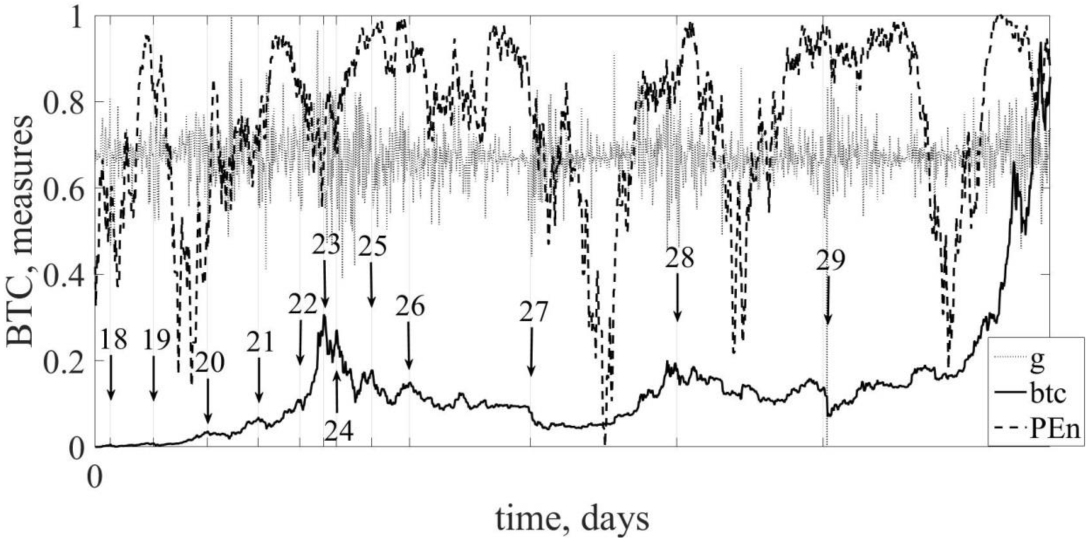


Fig. 4. Comparative dynamics of DJIA along with PEn calculated with rolling window of 500 days

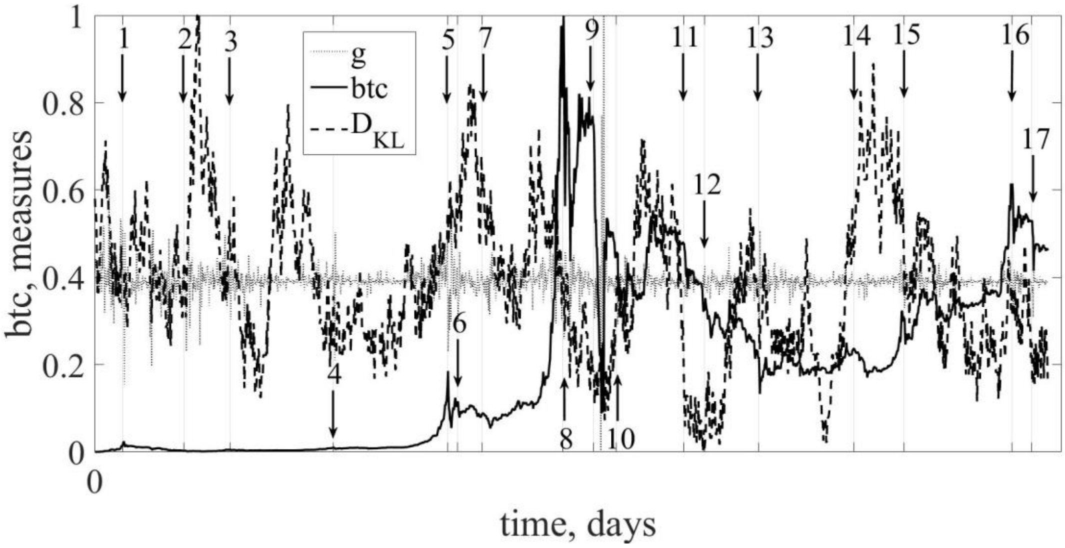


(a)

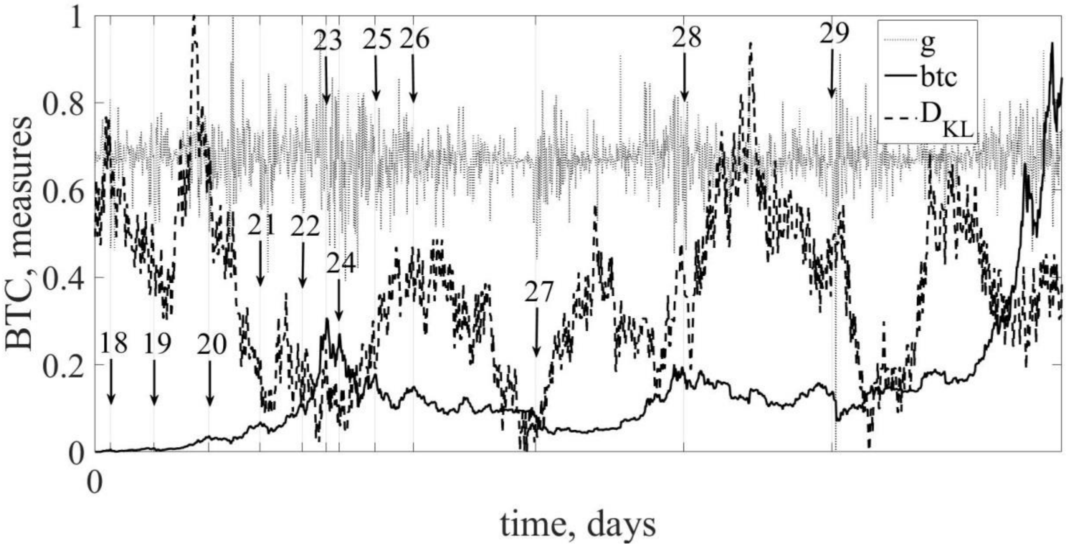


(b)

Fig. 5. Comparative dynamics of the first (a) and second (b) BTC periods along with PEn calculated for rolling window of 100 days and step size of 1 day



(a)



(b)

Fig. 6. Comparative dynamics of the first (a) and second (b) BTC periods along with D_{KL} calculated for rolling window of 100 days and step size of 1 day

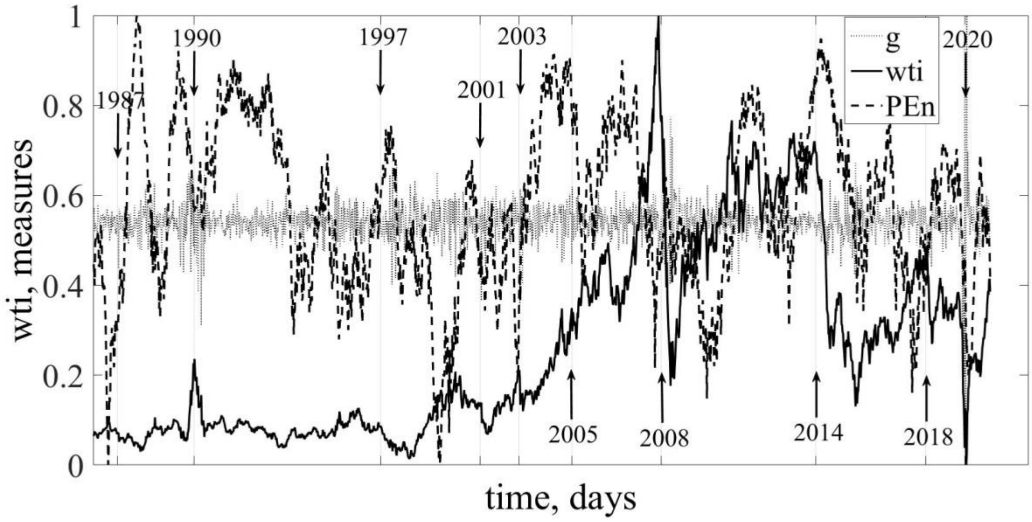


Fig. 7. Comparative dynamics of the oil price along with PEn calculated for rolling window of 250 days and step size of 1 day

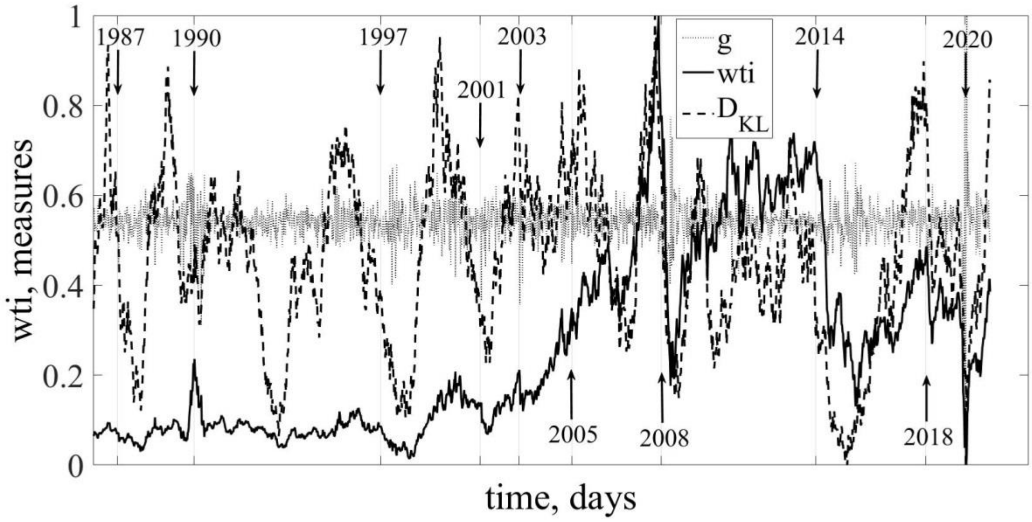


Fig. 8. Comparative dynamics of the oil price along with D_{KL} calculated for rolling window of 250 days and step size of 1 day

Empirical results present that discussed measures are able to distinguish completely random dynamics from deterministic (predictable). In the case of PEn, as this measure become higher, the complexity of the system increases and vise versa. For irreversibility measure based on permutation patterns we have more reversible dynamics for crashes or critical events and more irreversible for usual states.

Conclusions

The obtained quantitative methods were applied to emphasized crisis states in oil, crypto, and stock markets, where it was seen that these indicators can be used in order to identify critical changes in advance. To draw some conclusions about its evolutions and factors that influence it, we pointed out the most influential critical changes in this market.

Regarding empirical results, we could see that some of the measures are very sensitive to the length of the sliding window and its time step. For example, if we consider two closest to each other events, a previous event that had much more volatility can have a great influence on the corresponding measure of complexity or irreversibility and spoil the identification of the next less influential, but important event. Thus, time localization is significant while calculating the measure of complexity. The less time localization and time step, the more corresponding changes are taken into account. For a much larger time window and its step, we can have less accurate estimations.

Nevertheless, as we could see, both measures are presented to be robust and informative. Moreover, the predictive power of permutation entropy is even more characteristic in comparison with the indicator of irreversibility. In further, it would be interesting to test another types of entropies and irreversibility measures.

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