Qualifying Fluctuations in Economic Systems by Artificial Insymmetrised Patterns

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Abstract

Basing on features of time series that represent evolution of large and stable indices of world wide stock markets such as NYSE and S&P500, together with NASDAQ-the index that represents markets of new trends, we qualify properties of WIG - the index of the local stock market of Eastern Europe. The daily walks of indices WIG, NASDAQ, NYSE and S&P 500 for the last three years and last seven years are studied by patterns arisen from the artificial insymmetrised method.

Key words: econophysics, empirical study, visualization of data

1 Introduction

An Artificial Insymmetrised Pattern, AIP in short, was introduced by Pickover in 1986 [1] to describe human voice and animal vocalization. The method, called also Symmetrized Dot Patterns, takes advantage of the fact that symmetry, color and redundancy of dot patterns are useful in the visual detection and memorization of patterns by any human analyst. The method was successfully applied to many different time series [2], becoming a technique for the qualitative assessment of time series [3]. With AIP, one can graphically detect hidden patterns and structural changes in data or see similarities in patterns across the time series under study.

The fundamental assumption underlying the idea of AIP or any similar type propositions, like, e.g., recurrence plots [4], is that an observable time series is

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the realization of some dynamical process. Typically, we have interactions between many different factors over time which finally sum up into a one dimensional time series. An example of such process is a stock market. The behavior of the stock market is determined by many factors, such as the economic and political environment, investors expectations and individual trader's decisions. But eventually we deal a price of a stock.

In the following we present AIP plots for time series of indices of different stock markets. We consider properties of NYSE Composite (NYSE in short) and Standard and Poors 500 (S&P 500 in short) to obtain a picture of a well developed mature market. Warsaw Stock Exchange that just celebrated the 11th birthday in this April, is characterized by the index called WIG. The Polish market is a representative of so-called emerging market. We also look at NASDAQ Composite (NASDAQ in short) take care over a market related to the so-called "New Economy".

2 AIP method

By the AIP method we mean the way in which a one-dimensional time series is transferred into a two-dimensional space to visualize dependencies between two points of a series. This is done by converting a time series $\{x(n) : n = 1, 2, \ldots, N\}$ into a normalized to R series:

$$y(n; R) = R \frac{x(n) - \min_n\{x(n)\}}{\max_n\{x(n)\} - \min_n\{x(n)\}} \tag{1}$$

and then passing it into a complex plane by a following transformation:

$$\{z_\pm(n; R, \tau, \phi) = y(n; R)\; e^{\pm i[y(n+\tau; R)+\phi]}, \qquad n = 1, 2, \ldots, N\}. \tag{2}$$

Case of $-$ in (2) leads to the reflection of the $+$ pattern with respect to the horizontal axis. Moreover, for better visualization of regularities hidden in a time series, the sequence of phases is considered. Choosing $\phi_k = k\ (2\pi/m)$ with $k = 0, 1, \ldots, m-1$, one obtains m plots which are subsequently rotated by $k\frac{2\pi}{m}$. The τ parameter is introduced to observe the influence of the separation in time between points of pairs. Then, series $\{z_\pm(n; R, \tau, \phi_k)\}$ is collected as plots of plane points $\{(Re(z_\pm), Im(z_\pm))\}$, see [5] for AIP plots of some representative time series. AIP plots can be seen as return maps but plotted in polar coordinates.

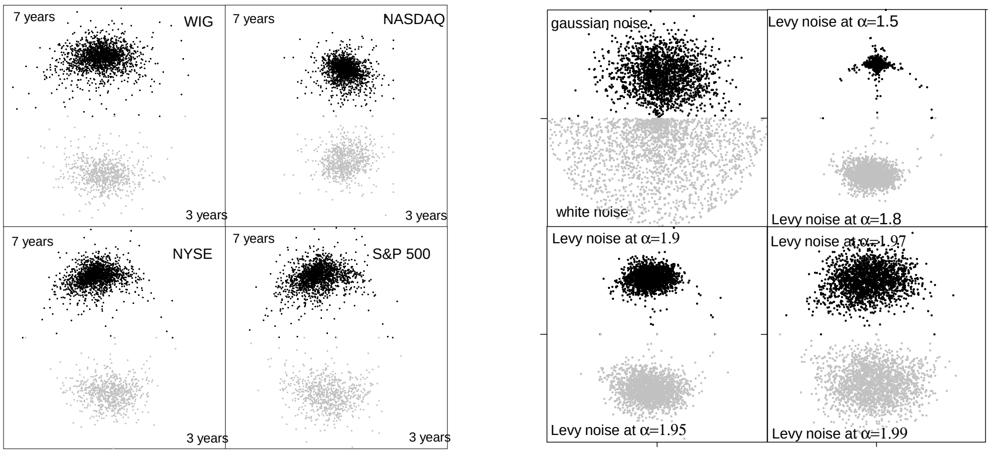

Fig. 1. Fat tails observed by AIP plots. On the left part there are returns of: WIG, NASDAQ, NYSE and S&P 500 for data of 7 (black dots) and 3 (gray dots) years. The right part is the AIP eye scale of noises: Gauss and white, and examples of Levy symmetric noises with different values of α.)2000 points are plotted in each pattern.)

3 AIP plots for market indices

The basic quantities studied here are values of indices: WIG, NASDAQ, NYSE and S&P500 at closing. For each time series we consider a series of daily returns defined as usual [6]:

$$\text{return}_{\Delta}(t+\Delta) = \ln[\text{index}(t+\Delta)] - \ln[\text{index}(t)] \tag{3}$$

The analyzed data comes from 1st January 1995 to 31st December 2001 (7 years study, about 1760 data points) or from 1 January 1999 to 31 December 2001 (3 years study, about 760 data points). In the following we decide to present time series normalized to $R = \pi$. So that, we have a half of π-radius circle for a single AIP plot. We resign from symmetries artificially introduced to AIP. Instead on one figure we show distinct AIP data to present better eye-catching differences. The gallery of different AIP plots for economic time series can be found in [5,7].

Rare events, which lead to the heavy tails in the distribution of returns [8,9], are represented on AIP plots as separated points located near zero - negative tails, and near the unit circle - positive tails. Presence of these events squeezes the "body" of AIPs making the area of the AIP plot much smaller than if the AIP plot is of a Gaussian noise, see Fig. 1. Comparing the localizations of

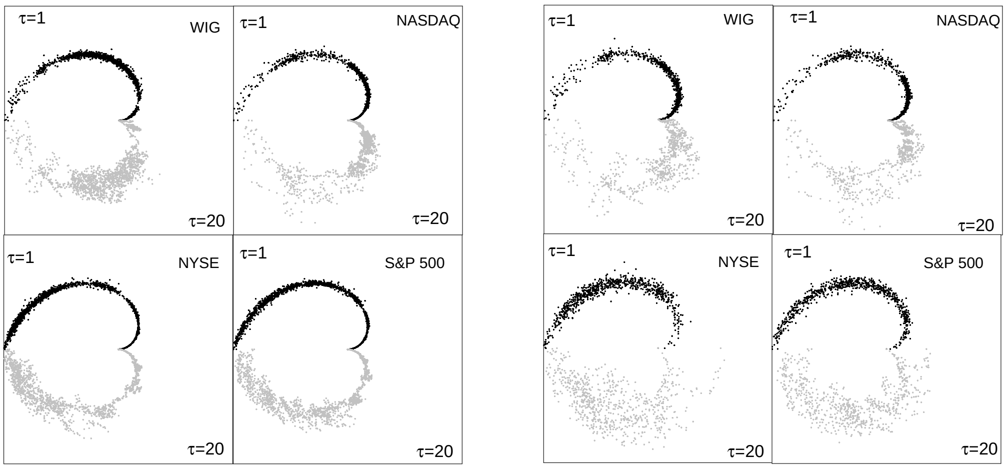

Fig. 2. AIP plots for walks of subsequent indices. Data comes from 7 years - left part and from 3 years -right part. The black plots represent one day delay, $\tau = 1$, the gray plots 20 days delay, $\tau = 20$.

main bodies of returns to examples of Levy noises, one can suggest that the returns are of the Levy noise type with $\alpha \approx 1.8$. However, plenty of dots are located away from the main bodies what indicates that returns are driven by a stochastic noise of the other type.

Figs 2,3 are to show development in time of indices. In general, they resemble the random walk plot. Surprising, the dependence on delay between points of a pair τ, see gray plots on Figs 2,3, is stronger in case of indices than it happens when a random walk is considered. Moreover, the AIP plots of 3 years NYSE and S$p500 walks in case when points separated by 20 days spread like a plot of white noise. This feature specially manifests in series of last three years and is not as evident when seven years time series are studied. This suggests that the market of NYSE and S$P500 has changed its regime last years. Furthermore, one can observe that the maximal values of WIG and NASDAQ are plotted as isolated points while in case of NYSE and S&P 500 the minimal values are isolated events. If we plot only parts of the AIP series, namely, the first 3 years data extracted from the 7 years AIP plot, then we can see the long-term trends in the indices walks. Such trends are not present if a random walk is observed, where each part of a random walk resembles the same shape. The walk of NASDAQ distinguishes from other series by a very long stay at its minimal values and a short fly to its highest value, see the right part of Fig.3. NASDAQ is explored by econophysics as an example of log-periodic time precursors that lead to a crush [10–12]. In the left part of Fig.3 we show the AIP plot of the log-periodic function $f(t) = t^{0.27}\cos[7.0\log(t)]$. This function has been found as describing time series of NASDAQ before

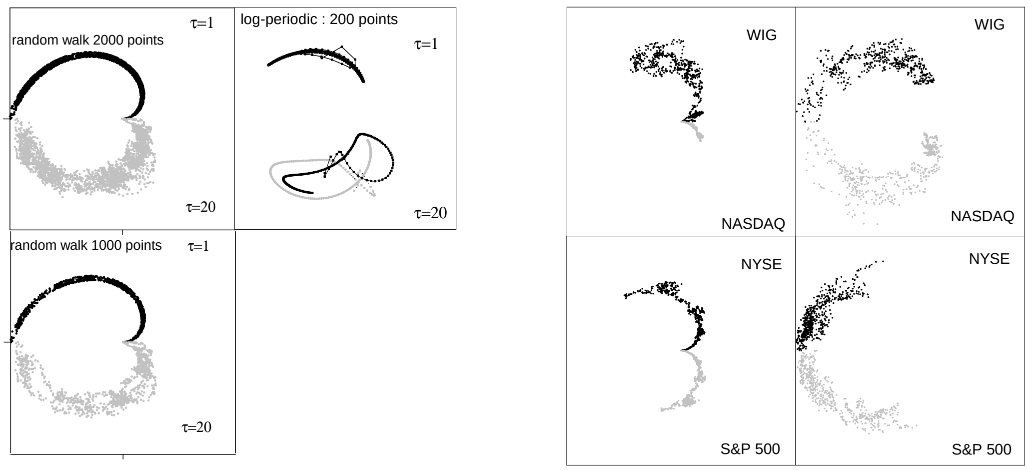

Fig. 3. Left part: AIPs for random walk and an example of log-periodic function with different time delay. The black plots represent one day delay, $\tau = 1$, the gray plots 20 days delay, $\tau = 20$. Right part: points of first three years (left panel) and then last three years (right panel) are extracted from AIPs of 7 years data of Fig.2 to show development in time, $\tau = 20$.

the crush of April 2000 [11]. At about the same time a rapid decrease of the index value took place on Warsaw stock market. However, difficulties were met while trying to describe this event by log-periodic oscillations [12]. But AIP figures suggest similar properties of both NASDAQ and WIG at that time and moreover these properties are distinct from time development of indices which did not feel the crush like NYSE and S&P500, see right part of Fig.3.

We do not find any significant dependence on τ when returns of indices are considered. The eye inspection suggests the lack of correlation between subsequent returns. However, since n-day returns: $\mathrm{return}_{n\ days}(t+n) = \sum_{i=0}^{n-1} \mathrm{returns}_{1\ day}(t+i)$, then one should expect the diffusion type dependence in the distribution of n-day returns. This dependence can be easily read from AIP plots, see Fig. 4. It occurs that in many-days time scale the AIP plots resemble a random walk.

4 Summary

We found that visualization of the economic data by the AIP method is particularly useful in getting into relations between markets. By comparing them to the scale plots we are able to observe general properties of fluctuations like heavy tails caused by the rare events or stability of the distribution of returns

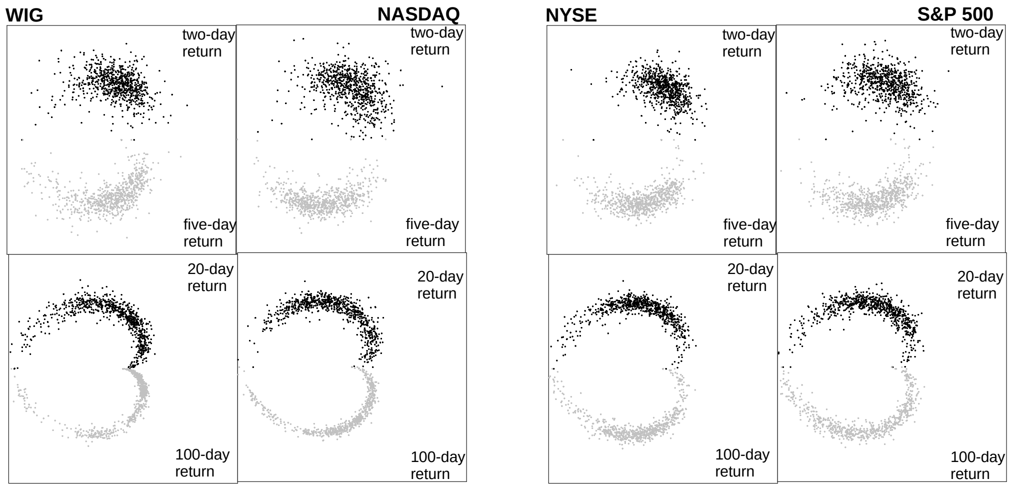

Fig. 4. Stability of returns by AIPs. On the left and right sides from top to bottom, returns of two-(black), five-(grey), 20-(black) and 100- days(grey) are shown

of particular indices as well as discrepancies from them. Since the procedure of plotting the AIP involves normalization of the data, we can compare markets. Moreover, as the AIP method keeps points in the time order, we can also easily find nonstationary features of markets. Therefore, we hope that simplicity of the method will make the method popular.

References

[1] C. A. Pickover, J. Acoustic Soc. Am. 8093, 112 (1986).

[2] C. A. Pickover, Computers, Patterns, Chaos, and Beauty, St. Martin's Press, New York, 1990.

[3] A. Posiewnik and J. Dąbkowski, Z. Naturforsch. 53a, 112 (1998).

[4] J. P. Eckmann, S. O. Kamphorst and D. Ruelle, Europhys. Lett. 4, 973 (1987).

[5] D. Makowiec and A. Posiewnik, Physica A 301, 429 (2001).

[6] P. Gopikrishnan, V. Plerou, L. A. N. Amaral, M. Meyer and H. E. Stanley, Phys. Rev. E 60, 5305 (2000).

[7] D. Makowiec and P. Gnaciński, Acta Phys. Pol. B 32, 1487 (2001); at the http address: //paula.univ.gda.pl/∼ fizdm/AIP/index.html

[8] B. B. Mandelbrot, J. Business 36, 394 (1963).

[9] R. N. Mantegna and H. E. Stanley, Nature 376, 4 (1995).

[10] A. Johansen and D. Sornette, Risk Magazine, **12**, 91 (1999).

[11] A. Johansen and D. Sornette, Eur. Phys. J. B **9**, 1671 (1999).

[12] A. Johansen and D. Sornette, Log-periodic power law bubbles in Latin-American and Asian markets and correlated anti-bubbles in Western stock markets: An empirical study - to appear in J. Theor. App. Finance (2001).