



Identifying financial crises in real time



Eder Lucio da Fonseca^{a,1}, Fernando F. Ferreira^a, Paulsamy Muruganandam^{b,c},
Hilda A. Cerdeira^{b,*}

^a GRIFE-Escola de Arte, Ciências e Humanidades, Universidade de São Paulo, Av. Arlindo Bettio 1000, 03828-000 São Paulo, Brazil

^b Instituto de Física Teórica, UNESP - Universidade Estadual Paulista, Rua Dr. Bento Teobaldo Ferraz 271, Bloco II, 01140-070 São Paulo, Brazil

^c School of Physics, Bharathidasan University, Palkalaiperur Campus, Tiruchirappalli 620024, Tamilnadu, India

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ABSTRACT

Following the thermodynamic formulation of a multifractal measure that was shown to enable the detection of large fluctuations at an early stage, here we propose a new index which permits us to distinguish events like financial crises in real time. We calculate the partition function from which we can obtain thermodynamic quantities analogous to the free energy and specific heat. The index is defined as the normalized energy variation and it can be used to study the behavior of stochastic time series, such as financial market daily data. Famous financial market crashes – *Black Thursday* (1929), *Black Monday* (1987) and the *subprime crisis* (2008) – are identified with clear and robust results. The method is also applied to the market fluctuations of 2011. From these results it appears as if the apparent crisis of 2011 is of a different nature to the other three. We also show that the analysis has forecasting capabilities.

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1. Introduction

Events such as market crashes, earthquakes, epileptic seizures, material breaking, etc., are ubiquitous in nature and society and generate anxiety and panic that is difficult to control. Preventing them has been the dream to which many scientists have devoted much of their work. There always exists the hope that mathematics can supply tools and methods for predicting when they will happen, but it is necessary to understand the processes that produce them. It is well known that complex systems can generate unpredictable outcomes while at the same time they present a series of general features that can be studied. The financial market dynamics belongs to this class; therefore using these tools may help to solve the problem.

The usual dynamics of the financial market shows investors sending orders on many different time scales, from high frequency (minutes) to long-term (years) transactions. To describe this, one needs to consider an enormous number of unknown variables, although this does not prevent us from finding some temporal correlation or patterns in the time series. To address these problems we shall use multifractal techniques known to capture non-trivial scale properties, as shown: by Mandelbrot (a pioneer in finding self-similarity in the cotton prices distribution [1,2]); by Evertsz [3], who confirmed distributional self-similarity and suggested that the market self-organizes to produce such features also; by Mantegna and Stanley [4], who found a power law scaling behavior over three orders of magnitude in the S&P 500 index variation. These works were important milestones in shedding light on financial market dynamics [5]. This shows that we can use concepts

* Corresponding author. Tel.: +55 11 3393 7852; fax: +55 11 3393 7899.

E-mail addresses: eder.luciofonseca@usp.br (E.L. da Fonseca), ferfff@usp.br (F.F. Ferreira), anand@cnld.bdu.ac.in (P. Muruganandam), cerdeira@ictp.trieste.it, cerdeira@ift.unesp.br (H.A. Cerdeira).

¹ Present address: Instituto de Matemática Estatística, Universidade de São Paulo, Rua do Matão, 1010, 05508-090 São Paulo, SP, Brazil.

and tools from statistical mechanics to model and analyze financial data [6–13]. From there on, many researchers gathered evidence that there exist alterations in the signal properties preceding large fluctuations in the financial market [14–20].

In this work we develop a new measure, the area variation rate (AVR), designed with the goal of identifying financial crises in sufficient time to take necessary steps. We do not attempt to explain the reasons for the crises, which are beyond our scope, but aim simply to introduce a systematic way to look at the data which may help to distinguish systemic fluctuations – intrinsic to the dynamics dictated by the internal interactions – from those generated by external inputs [21,22].

We handle time series in order to detect informational patterns in such a way that it is not necessary to know the complete series, only past data, in contrast with well established methods such as mutual information and others [23–25]. This will make our approach particularly useful for all practical predictive purposes. It will be shown that our method gives some striking results when applied to the financial market.

Our work is based in that of Canessa [26], who adapted calculations of time series to previous results of Lee and Stanley [27] on diffusion limited aggregation. In the latter, motivated by the analogy with thermodynamics, a partition function is calculated, such that the elements are the probabilities of given events, which in our case will be increments in the time series. Applications of this method can be found in the works by Kumar and Deo [28], Redelico and Proto [29] and Ivanova et al. [30]. This analogy will allow us to call some quantities by the names of the corresponding thermodynamic variables, although keeping in mind that this is just a convenience.

2. Analysis of market data

In order to analyze the data we proceed as follows:

Given a series of N elements $x(t)$, we determine the increments $\Delta x(t, T) = x(t + T) - x(t)$, where $t = 1, 2, \dots, N$ and T is an adjustable quantity. We define a measure [26,27]

$$\mu_t = \frac{|\Delta x(t, T)|}{\sum_{t=1}^N |\Delta x(t, T)|}, \quad (1)$$

and a generating function (partition function) as a sum of the q th-order moments of this measure [27]:

$$Z(q, N) \sim \sum_{t=1}^N \mu_t^q \sim N^{-\tau(q)}, \quad (2)$$

where

$$\tau(q) = (q - 1)D_q, \quad (3)$$

$\tau(q)$ plays the role of a free energy, and D_q is the fractal dimension of the system. $\tau(q)$ is related to the generalized Hurst exponent [28,31,32] and to the Rényi entropy [33]. Following this path, Canessa [26], seeking to model economic crises with nonlinear Langevin equations, showed that for financial market data the quantity

$$C_q = -\frac{\partial^2 \tau(q)}{\partial q^2}, \quad (4)$$

presents special effects when the string of economic data include those of a crash. We shall refer to this quantity as the *analogous specific heat* (ASpH). Using the S&P 500 data corresponding to the 1987 market crash known as *Black Monday* (BM), it has been shown in Ref. [26] that these curves present two lobes when the time series of N elements contains the datum point of the crash. Further, the maximum of ASpH, $C(q)$, diminishes when the single datum point from the day of the crash is removed and disappears when the data for the neighboring days are deleted [26]. This lobe is due to the presence of large fluctuations ($q > 0$) in the portion of the time series calculated. In Fig. 1 we show accumulated curves for $C(q)$ for Dow Jones data for windows of time before and after the crash; in particular Fig. 1(a) represents the accumulated curves for 50 days before the crash and Fig. 1(b), those for 50 days after – and including – the crash. The dotted curve corresponds to BM. Further on in the text we will complete the description of these curves.

To study the differences in the ASpH along the complete time series of size L , let us consider a window of size N as a section of the series to be analyzed. This window is shifted along the data, with a given shift l , less than or equal to N . T , N and l are parameters to be chosen for the particular system under consideration and the values are not predetermined. They are chosen as the best set for a given type of data; their selection will depend on the stability of results which will be discussed below. We calculate the area under the curve of ASpH, which we call $A(n)$, where n is the index that identifies the window in which our calculation is done, that is the number of shifts that we performed. To identify the corresponding index in the complete series we notice that

$$t'_n = t_0 + N + nl, \quad (5)$$

where t_0 is the time where the calculation starts, and $n = 1$ corresponds to $t'_1 = t_0 + N$ for the series considered. Since the areas are calculated over a long period of time, they possess a long memory, which is not necessarily desirable when we are

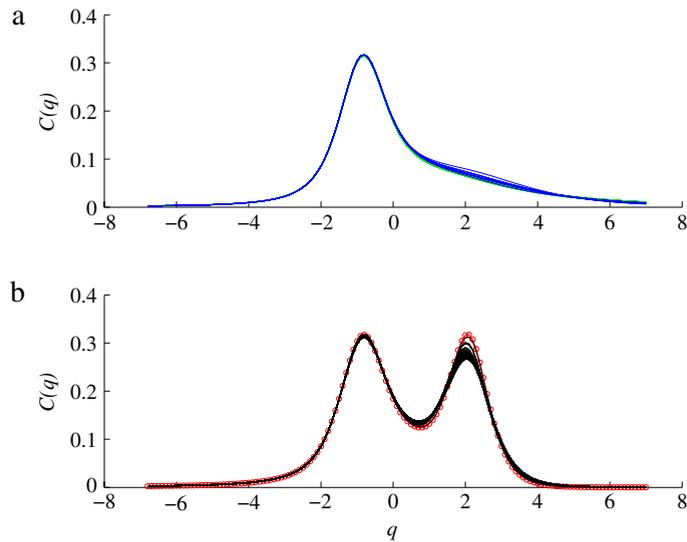


Fig. 1. Accumulated analogous specific heat, $C(q)$, for the crisis of 1987, Dow Jones index; (a) 50 days beginning with *Black Monday* (19 October 1987), (b) 50 days after *Black Monday*. Dots correspond to BM. Here $N = 1000$, $T = 1$ and $l = 1$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

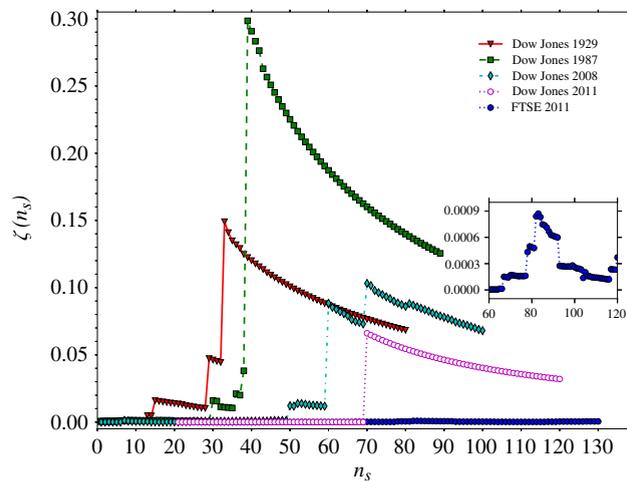


Fig. 2. Plot of the area variation rate $\zeta(n)$ for the daily index for different events: the crash of '29, where $n_s = 30$ corresponds to 24 October 1929 (red triangles) and $n_o = -20$; the crisis of '87, where $n_s = 40$ refers to 19 October 1987 (green squares), $n_o = -10$; the crisis of 2008, where $n_s = 50$ represents the bankruptcy of Lehman Brothers (cyan diamonds) and $n_o = 0$; the events of 2011—we show the AVR of the Dow Jones data, where $n_s = 70$ corresponds to 5 August 2011 (lilac empty circles) and $n_o = 20$ and that of the FTSE100 series, which is not noticeable in this graph (blue filled circles), $n_o = 30$. For this case we have used $T = 1$, $l = 1$ and $N = 1000$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

near a crash or in a succession of them. In order to obtain seemingly uniform information we define the area variation rate (AVR) $\zeta(n)$ as

$$\zeta(n) = \left| \frac{A(n)}{\bar{A}} - 1 \right|, \quad (6)$$

where the mean \bar{A} is calculated over all the windows previous to n . When there is no particular event in a time series, this parameter fluctuates around or below 10^{-3} —see the inset in Fig. 2. Although we do not have any proof, this seems to be always the case and it agrees with the AVR generated by white noise, as will be seen below.

To apply this method we use daily closing indexes from different markets: Dow Jones, DAX, FTSE100, CAC, S&P 500 and Nasdaq, although not all results are shown. The data set was obtained from finance.yahoo.com. The complete URLs and the dates of downloading of the data are given in Ref. [34]. The AVR for financial market daily data over a period of 100 days is drawn in Fig. 2 for several well known events: the crises of 1929, 1987, 2008 and 2011. All plots start 50 days before the event that history identifies as the day of the corresponding crash, as was done for Fig. 1. Thus, all the data used for the

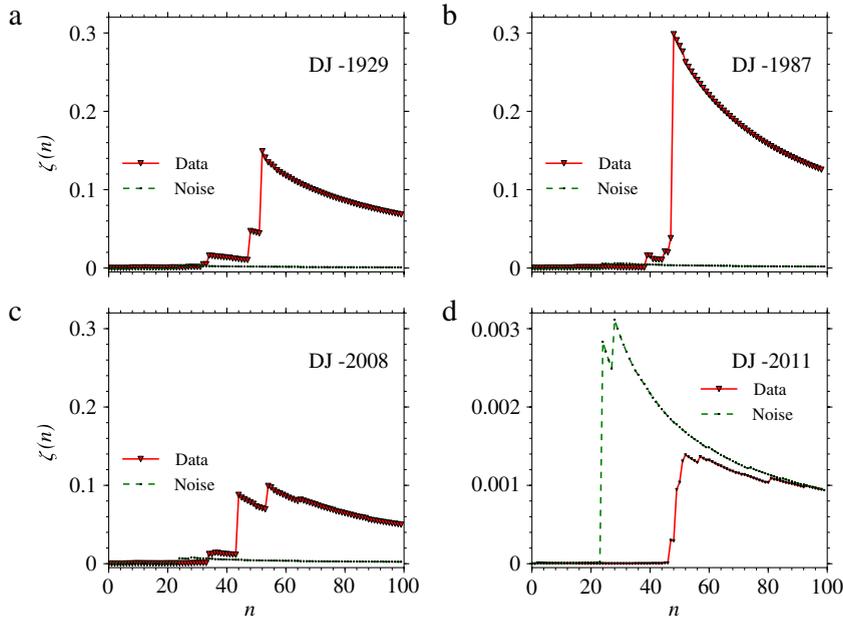


Fig. 3. Plot of the area variation rate $\zeta(n)$ for the Dow Jones daily index and for randomly generated time series with the same average and variance as the corresponding Dow Jones index with parameter values $l = 1$, $T = 1$, $N = 1000$ for: (a) the crash of 1929; (b) the crash of 1987; (c) the subprime crisis of 2008; (d) data centered around 5 August 2011.

calculation of the AVR for a given day are prior to the date. In order to be able to notice their common features as well as their differences, all the curves are plotted in the same graph with shifted origins (n_0). The crash of '29 is shown in red triangles, where $n_s = n + n_0 = 30$ corresponds to 24 October 1929, known as *Black Thursday* (BT). The curve in green squares plots the same data, and $n_s = 40$ marks 19 October 1987, or *Black Monday* (BM). Next, in cyan diamonds, we present the same parameter AVR for the financial crisis of the year 2008, which was called the *subprime crisis*, and compared by the press to the crash of '29. Although there is a jump in the curve, it is well below the other curves. The value of $n_s = 50$ corresponds to 15 September 2008, when Lehman Brothers announced bankruptcy, an event which may have produced the successive jumps at $n_s = 60$ and $n_s = 70$. Next, given in lilac empty circles is the area variation rate for the Dow Jones 2011 data, where $n_s = 70$ corresponds to 5 August. This date was chosen since on that day Standard and Poor's announced the decrease in the credit ratings of the United States [35]. Therefore it is only natural to expect some reaction of the market. This is the only event worth mentioning in the Dow Jones data during 2011. Finally, in blue filled circles we show the FTSE100 during 2011, which stays below 10^{-3} throughout the year (partially shown in the inset of Fig. 2). Besides the Dow Jones and FTSE100, we analyzed other European markets for 2011: DAX (Germany) and CAC (France). All of them except the FTSE100 have some fluctuation above average in the summer of 2011 and a noticeable jump around 6 December 2011—the day when the results of a discussion on the survival of the Euro were announced. All fluctuations are within the same order of magnitude but below 1.5%.

From that figure we notice that the AVR rises above noise at least one week before the crash for 1929, 1987 and 2008, a characteristic that may be used as an indicator of the coming event. There is no significant fluctuation in the AVR during 2011. To discern whether the increase is related to the crash we compare these results with the AVR index of a randomly generated time series (noise). The data used to calculate the AVR of the noise were obtained from a long series generated from white noise (independent and normally distributed), with the same mean and variance as the corresponding Dow Jones index. A value that “rises above noise” is at least one order of magnitude larger than these fluctuations. Results for the four cases discussed previously can be seen in Fig. 3. It is interesting to notice that the noise and 2011 fluctuations are of the same order of magnitude.

To interpret the importance of the AVR in the identification of crises, we recall that in Fig. 1(a) and (b) we show the accumulated curves for the ASPH individually calculated over each window of length N previous to the point n . When we move to $n + 1$, we slide the window onwards by a quantity l (shift) and calculate $C(q)$ again. There are 50 overlapping curves in each figure and they are of both types: with single and doubled lobes. There is a clear change of shape in the curve corresponding to BM, already identified by Canessa by exclusion of the crash day's data in his calculation. The distinct shape that the curve has on the 19th October shows the sensitivity of the method to the inclusion of the data for the crash since it is only one point within N that produces a dramatic change in the figures. But the most important feature in the identification of the crisis is that the second peak of the curve $C(q)$, for $q > 0$, appears at the same moment as the curve AVR jumps, and it appears only if the jump is large, thus clearly pointing to the crash, which is produced by the very large

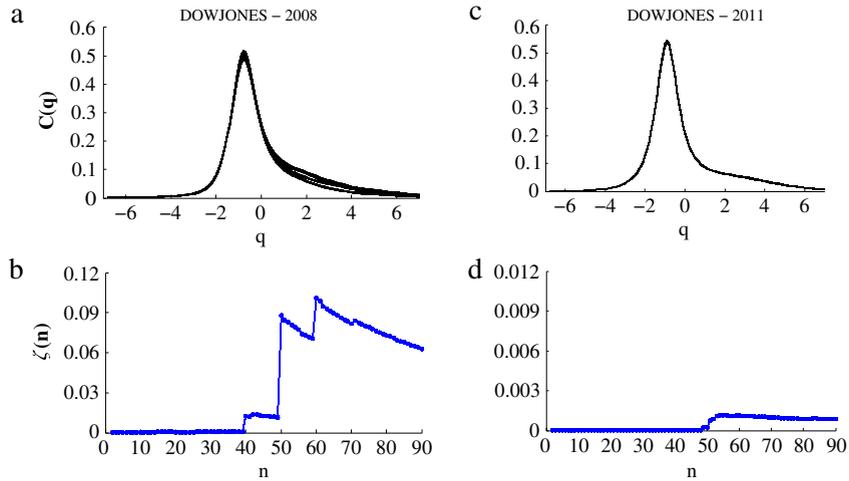


Fig. 4. (a) Analogous specific heat, $C(q)$, for Dow Jones data corresponding to the subprime crisis, 2008. (b) Plot of the corresponding area variation rate, $\zeta(n)$. (c) $C(q)$ for Dow Jones 2011. (d) Plot of the area variation rate, $\zeta(n)$, for 2011; the jump corresponds to 5 August 2011. All curves were calculated with $l = 1, T = 1, N = 1000$.

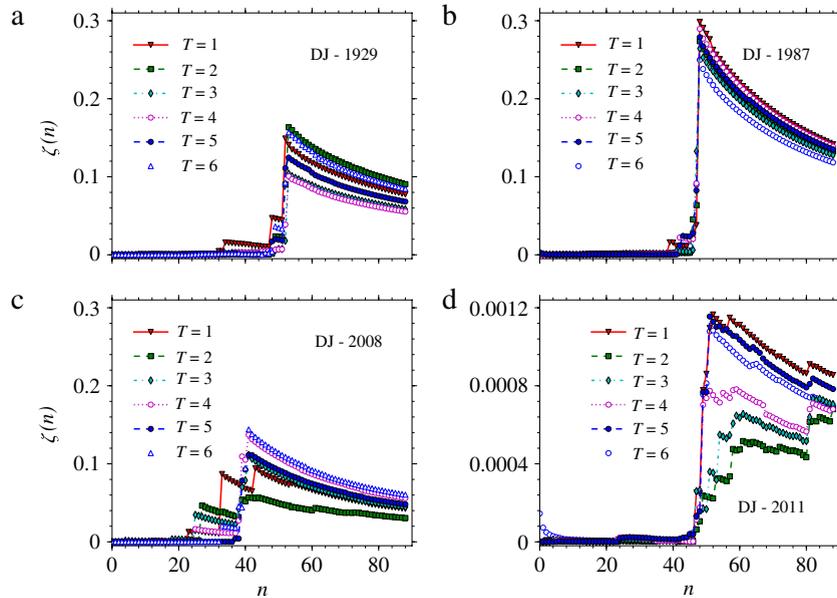


Fig. 5. Area variation rate, $\zeta(n)$, as a function of n , for different values of T : (a) the Dow Jones crash of October 1929; (b) the Dow Jones crash of October 1987; (c) the Dow Jones subprime crisis of 2008; (d) Dow Jones August 2011. All curves were calculated with $l = 1$ and $N = 1000$.

fluctuations. Therefore large fluctuations in the market data give rise to the second maximum in the ASPH, which gives rise to a discontinuity in the AVR, while robustness against N, T and l helps to identify a crisis.

Next, we analyze the accumulated curves $C(q)$ for all the cases shown in Fig. 2; we have found a clear second lobe for the crises of '29 and '87. In particular let us focus our attention on the accumulated ASPH calculated along n for 2008 and 2011 (Fig. 4(a) and (c), respectively) and the corresponding area variation rate as a function of n — Fig. 4(b) and (d), respectively. There is no well defined second maximum in ASPH for 2008, although the results are robust against changes in N and T (not shown). For 2011 we detect no significant jumps in the AVR nor changes in the ASPH, and the results do not persist under changes in the parameters (shown next).

A small size window may produce false positives. Investigating the Dow Jones data over a century, it is noted that sometimes the AVR presents unexpected jumps. However, most of those jumps do not exhibit the pattern observed for the famous crashes and the jumps tend to vanish on increasing the window size N and T . In Fig. 5 results are shown for the AVR for all cases when varying the time lag. Results for 1929, 1987 and 2008 remain stable. For 2011, the jump on 5 August changes shape while staying always below or around the noise level. We show similar results but varying N in Fig. 6, starting at a very low window size, $N = 100$ for 1929. The AVR rapidly converges to a final value for 1929, 1987 and 2008.

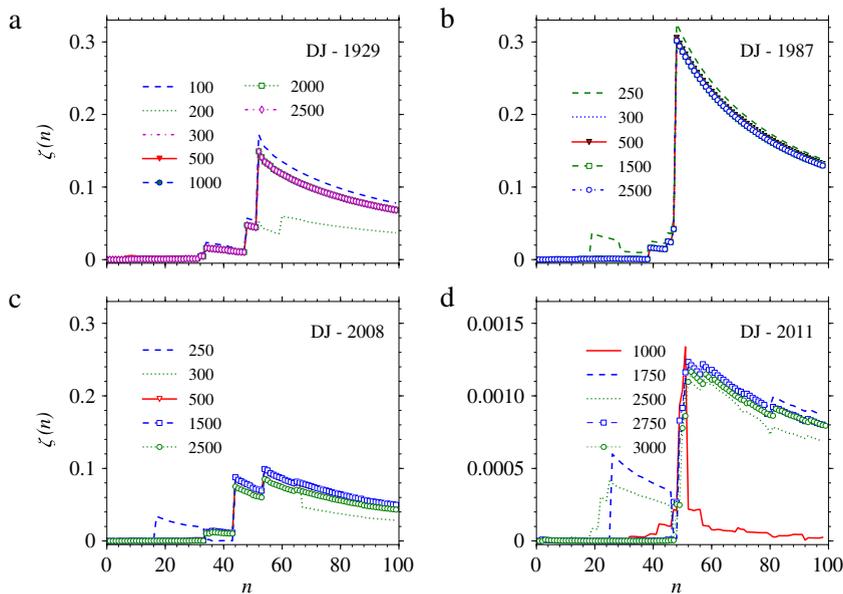


Fig. 6. Area variation rate, $\zeta(n)$, as a function of n , for different values of N : (a) the Dow Jones crash of 1929; (b) the Dow Jones crash of 1987; (c) Dow Jones 2008; (d) Dow Jones August 2011. All curves are calculated with $l = 1$ and $T = 1$.

That for 2011 oscillates without ever reaching a stable value. Another important factor is that the features previous to the crash discussed before appear for all values of N and T with $T = 1$ giving the best results. Most features disappear when the shift l becomes of the order of N , which is expected. From these findings, it appears as if the crisis of 2011 is of a different nature to the other three. Calculations for different parameters N and T will show a real crisis, real being defined as stable against variations of N , T and l , by comparison with the events historically recognized as crises.

3. Summary

Summarizing, we have presented a method by which market crises can be identified and distinguished from simple scares, which could avoid diffusion of panic. We noticed that when a crisis is systemic it behaves as in the cases well recognized historically as crises. It is usually accompanied by a sizable increase in the area variation rate, by several orders of magnitude. It corresponds to a crash only if the analogous specific heat also presents a second maximum. Finally, all results are stable under changes in N , l and T . We notice that for some well known crisis such as the crashes of '29 and '87, the AVR already shows a substantial increase above noise almost two weeks before the event, creating expectations as to the possibility of being used as a warning signal. While it is quite clear that the existence of large fluctuations ($q > 0$) produces stable jumps in AVR, the predictive ability of the algorithm seems to depend on the values of T . An important factor of this method is that all calculations are done using data preceding the singular event, thus making it extremely useful, in particular for medical cases such as epilepsy. Its identification through an electroencephalogram, performed by the recognition of a specific characteristic of the temporal series, is only done after the episode. A method based on the calculation of the AVR may help in predicting seizures. Although this is not a tool which can help to avoid crises, due to the simplicity of its use it can be implemented to monitor economic or physiological data when there is a possibility of a crisis. More research is under way to study applications – in particular the possibility of foreseeing epileptic seizures – and to establish the algorithm on a sound mathematical basis.

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