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Identifying financial crises in real time

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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.

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

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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 $t = 1, 2, \ldots, N$ and T is an adjustable quantity. We define a measure [26,27]

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

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

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

where

$$\tau(q) = (q-1)D_q, \tag{3}$$

$\tau(q)$ 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

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

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

$$t'_n = t_0 + N + n\,l, \tag{5}$$

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