Forecasting intraday movements in the stock market using wavelets

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Abstract

Methods to anticipate movements in the stock market are essential to determine the best moment to buy and sell stocks, options and indexes. Forecasting significant abrupt movements can be of paramount value to investors in order to avoid financial crisis. Since the famous event of 1929, several mathematical models have been proposed to try to forecast the occurrence of these movements. The main idea in this work is to adapt a method developed earlier by the authors using wavelet transform to anticipate intraday changes in the stock market. Because it is not an easy task to infer imminent price movements by simply examining the relative values of the coefficients resulting from the wavelet transform, an indicator is proposed in the form a real number between 0 and 1. The parameters of the algorithm to compute the proposed index was tuned using pre-down and pos-down data windows along a large record of Brazilian Stock Market Index (Ibovespa) and some options of Brazilian firms. Some statistical data are pesented to show the efficiency of the proposed indicator.

Keywords: Forecasting, Intraday, Stock markets, Wavelets, Indicator

1. Introduction

Following the famous financial crises of 1929, sustained efforts have been directed to investigate and elucidate the causes of this type of event, in the hope forecasting eventual occurence of new financial turmoil (Edie, 1930; Burgess, 1930; Brunner & Meltzer, 1968). It is now a common sense that crashes are not usually due to a single root factor but the confluence of many different effects as pointed out by many authors (White, 1990; Rappoport & White, 1993, 1994). Finding a bubble event in a stock market is not an easy task and estimating the probability of next event have strong impact in other episodes of crisis. In Sornette (Sornette, 1996, 1997, 1998, 2003) and Johansen (Johansen, 2001[a] , 2001[b] , 2003), one can find a method to anticipate the onset of abrupt changes in the stock prices based on precursory patterns and with characteristic log-periodic signatures that resembles the waveforms associated with imminence of earthquakes. In a previous work (Caetano & Yoneyama, 2007, 2009) the authors have proposed to use the wavelet decomposition technique to detect the dominance of high frequency components in the time series using daily data and proposed an indicator, consisting of a real number between 0 and 1, which tends to reflect the imminence of abrupt changes in the prices. However, it is possible to observe that the oscillations of prices during the day cause fluctuations that can be the causes of great drawdown or the start for a new financial crisis. The movement known as high-frequency type in the stock market anticipates the abrupt changes of prices.

Intraday business are highly sensitive to reports, news and comments about the state of the economy or of a specific firm. The periodicity of fluctuations and volatility are normally analyzed using mathematical models such as ARCH and GARCH among others. Bollerslev (Bollerslev *et al.*, 2000) discuss how reports and news can influence the behavior of financial markets. These changes can be of random nature or can following a natural business trend during the day. Gençay (Gençay *et al*., 2001) uses multi-scaling technique based on wavelets to find possible seasonality during intraday business. Karuppiah (Karuppiah and Los,1997) also uses wavelet to analize and indentify high-frequency components in the Asian market.

2. Abrupt changes in intraday business

In the literature one can find a variety of mathematical models to explain movement of prices in the stock market. For instance, Chen (Chen, 1996) discusses whether the movement of prices can be modeled using random-walk or color-chaos concepts. Bischi (Bischi and Valori, 2000) present a discrete nonlinear mathematical model to represent the dynamics of the stock market. More recent techniques uses artificial intelligence tools such as neural nets and fuzzy logic (Gradojevick *et al*, 2002).

In this work, the idea is to use the wavelet decomposition technique to provide simultaneous information on the frequency (scale) and localization in time (translation), so that chirp like signals, as used in Sornette et al, 1996, 1997, 1998 can be easily analyzed. More specifically, oscillating components with long and short periods, at any given instant of time, can be represented in a scales × time chart, where values of the components can be represented by shades of grey. In this way, the shades form patters that dislocates in time, so that one can be alerted of the possibility of an abrupt change in the stock prices.

Orthonormal wavelets can be used as a basis to represent a function in an expanded form, in a procedure that is analogous to that of expressing a periodic function as sums of sines and cosines with appropriate weights or coefficients. The functions in a family ψ of wavelets can be obtained by scaling and translating a single function φ, called mother wavelet (see Daubechies, 1992; Meyer, 1993). Hence, if the function φ is a mother wavelet, then the family ψ is constructed using scaling $a \neq 0$ and translations b

$$\psi \overset{\Delta}{=} \left\{ \varphi^{a,b}(.) \in L^2(R);\ \varphi^{a,b}(t) = |a|^{-1/2} \varphi\left(\frac{t-b}{a} \right), a \in R, b \in R \right\} \tag{1}$$

where $L^2(R)$ denotes the set of square integrable functions, i.e., $\left\{ f : R \to R \text{ s.t. } \int_{-\infty}^{\infty} |f(t)|^2 dt < \infty \right\}$. When b = 0, then the parameter 'a' simply stretches or shrinks the waveform in the direction of the t-axis. On the other hand, when a = 1, b simply moves the waveform along the t axis.

Under adequate hypothesis ψ constitutes a basis for $L^2(R)$ and the wavelet transform is obtained as the inner product of the function to be expanded, $f \in L^2(R)$, with $\varphi^{a,b} \in \psi$, for each a and b:

$$W_f(a,b) = \int_{-\infty}^{\infty} f(t) \varphi^{a,b}(t) dt \tag{3}$$

In other words, given $W_f(a,b)$, f can be recovered by the formula

$$f(t) = \frac{1}{C} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_f(a,b) \varphi^{a,b}(t) dt \tag{4}$$

where the constant C depends on the mother wavelet:

$$C = \int_{-\infty}^{\infty} \frac{|\hat{\varphi}(\omega)|^2}{|\omega|} d\omega \tag{5}$$

Among many possibilities for the choice of the mother wavelet $\varphi(.)$, the Mexican Hat Wavelet function from *MATLAB 6.5* © was adopted in this work. The general behavior of the wavelets coefficients are independent of the particular choice of the mother wavelet in the sense that the smaller scales become prevalent in the imminence of drawdown.

Although the occurrences of drawdowns were successfully detected by Caetano & Yoneyama (2007) using the wavelet transform, it required a visual analysis of a graph with the wavelet coefficients represented by shades of grey varying from black to white, for each pair (time, scale) of points, thus forming a pattern ("tornado"). For instance, in case of daily data of financial crisis 1929 for Dow Jones (figure 1), this shaped pattern is in figure 2 with the presence of high-frequency signals.

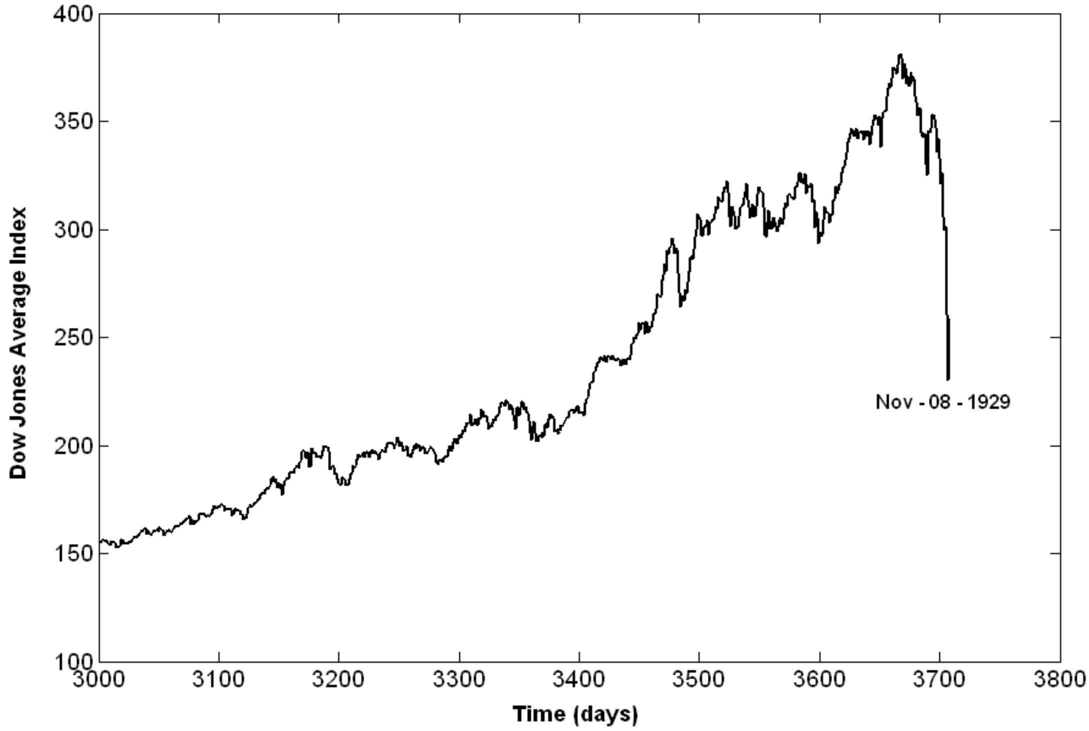

Figure-1 Dow Jones Average (DJA) index showing the crash of 1929

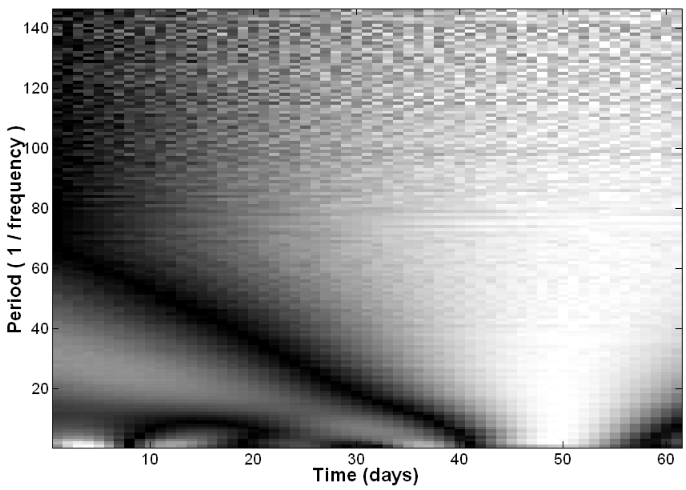

Figure-2 Wavelet decomposition for DJA pre-crash data of 1929.

Instead of using shades of gray as shown in the graph of figure 2, one can count the number of coefficients with values that are greater than a convenient threshold in a rectangular region of the graph (the right of figure 2 with a small time range) and compute an index defined by

$$\zeta(t) = \frac{n(t)}{N} \tag{6}$$

where N is the total number of coefficients in the strip and n(t) is the number of coefficients greater than the adopted threshold. The variation of ζ lies in the interval [0,1]. For instance, in case of Ibovespa intraday-15 min was adopted threshold as 2000. Then, *n(t)* is total numbers of coefficients that are higher than 2000 in the last column.

Observing a number of financial time series, one can notice that if ζ is close to 1, the probability of a drawdown is high and if ζ is close to 0, the market maintains its current trend. Because the task of interpreting patterns formed by shades of grey requires subjective criteria, this work proposed an indicator (a real number between 0 and 1) that is related to the probability of imminent drawdown.

As an example, consider the Brazilian Stock Index (Ibovespa) data of 15 minutes from October 2009 up to the February of 2010. The linear trend is given by

$$y_L(t) = 5619 + 2t \tag{7}$$

with t in periods of 15 minutes of acquisition data and the cyclic term by

$$y_C(t) = -2029 \times \cos(0.0025\,t - 10.1) \tag{8}$$

Applying the wavelet decomposition to the series $y(t) - y_L(t) - y_C(t)$ and computing ζ (t), one obtains the results shown in figure 3 and figure 4. It can be noticed that ζ (t) rises sharply with a small delay with respect to the starting point of the drawdown. The method can yield small positive indication, as seen in figure 4, which is around 0.1. In the other hand, one can notice a significant volatility following the raise of ζ(t) due to oscillation of movement prices during the day.

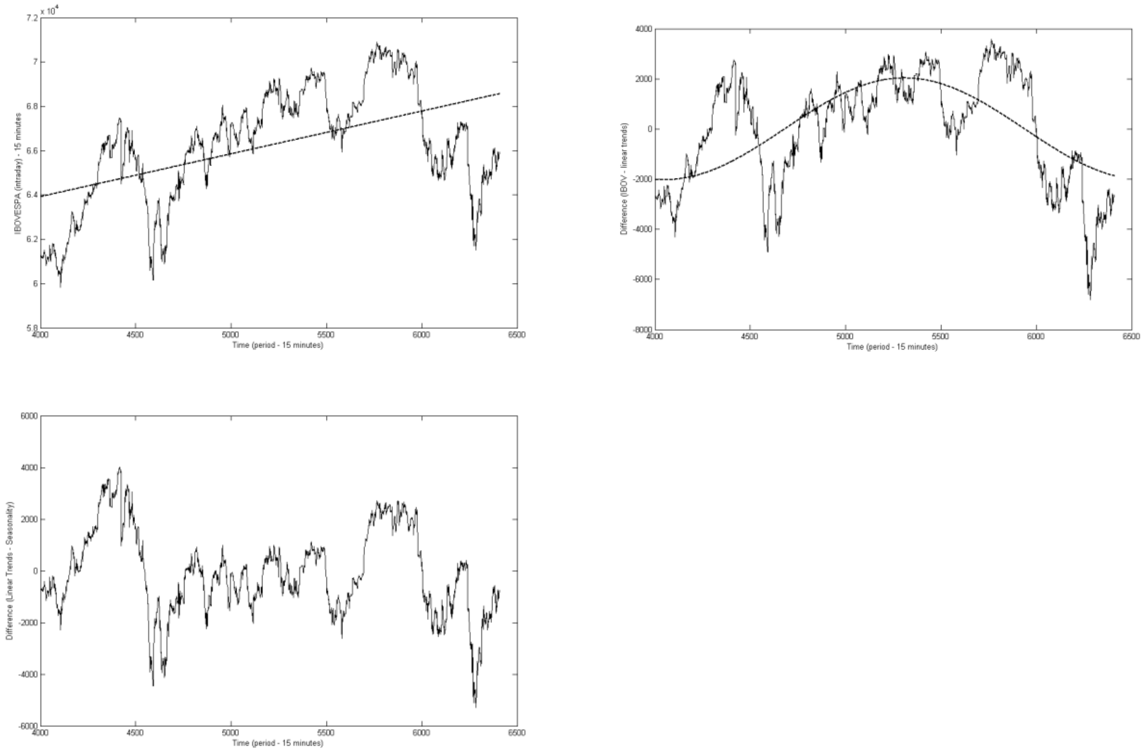

Figure-3 Upper Left: Original Ibovespa(intraday 15 min) and Linear trend; Upper Right: Cyclic component; Lower Left: Ibovespa-15 min data with the exponential and cyclic trends removed in order to satisfy the conditions required for wavelet decomposition.

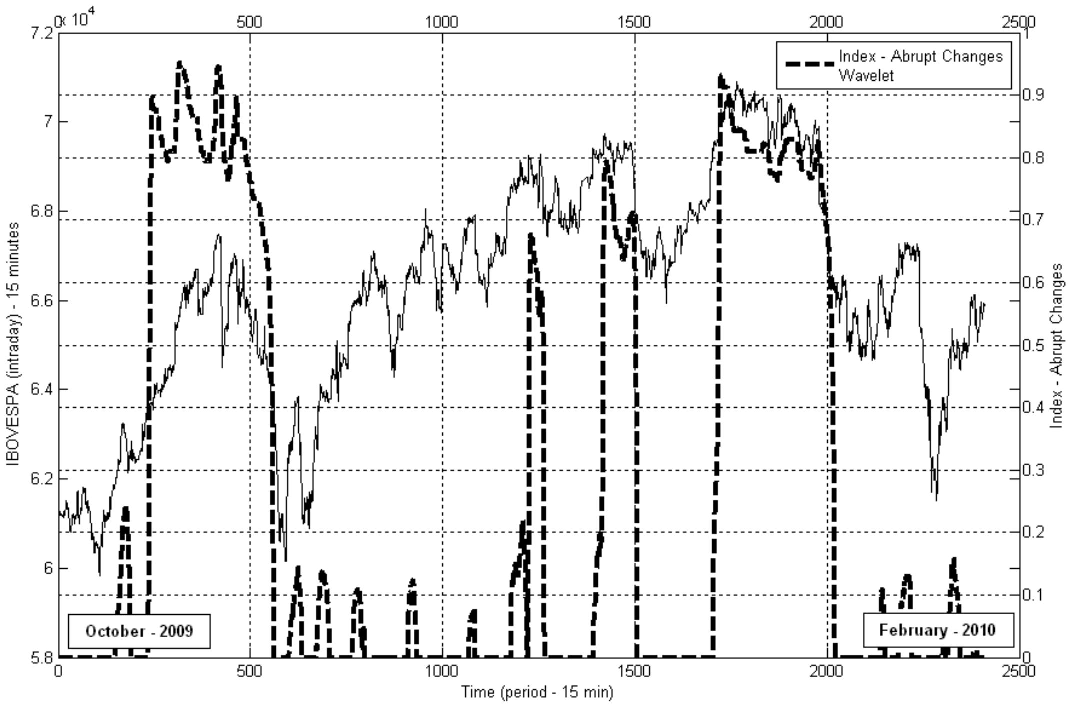

Figure-4: IBOVESPA Index (left axis) and the proposed index (Wavelet Index in the right axis) with dot-line.

As an application of the method to other type of time series, data on options offered by the biggest two Brazilian firms were selected (PETROBRAS and VALE). The figure 5 shows the data for option VALEB42 of “Vale do Rio Doce” and figure 6 shows the data for option PETRL40 of “Petrobras”. In both graphs is possible notice good precision in alerts near to abrupt changes of prices. Always when the index approaches one (right side y-axis) the prices change the trend and begin to fall.

Table-1 Statistics of Alarms for Ibovespa- Intraday – 15 minutes

Days of Observation – Ibovespa (intraday)	**223**
Signals of alarm	**22**
True alarm	**15 (69%)**
False alarm	**7 (31%)**
Average - down	**-2.42%**
Maximum - down	**-6.6%**
Minimum - down	**-0.08%**
Average – False Alarm	**+1.46%**
Maximum – False Alarm	**+2.3%**
Minimum – False Alarm	**+0.2%**
Average Time to minimum value	**2.97 days**
Maximum Time to minimum value	**7.4 days**
Minimum Time to minimum value	**30 minutes**

The Table-1 presents the statistics for alarms indicated by the wavelet index with data from Ibovespa acquired each 15 minutes during 223 days. The total number of data is 2805 with 22 alarms signals emitted during this period. It is possible to notice that 68% are true positives against 31% false alarms.

One important data is the expected waiting time until the end of the fall (2.97 days).

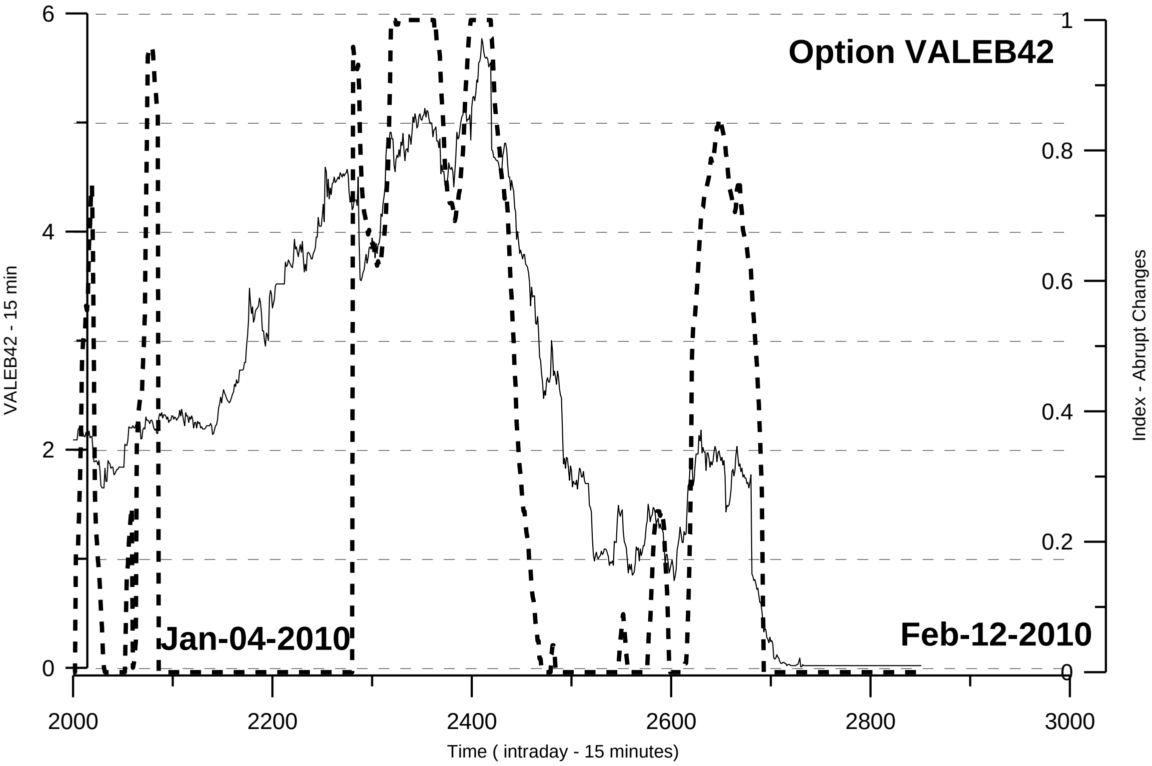

Figure-5: VALEB42 options (left axis) and the proposed index (right axis) in dot-line.

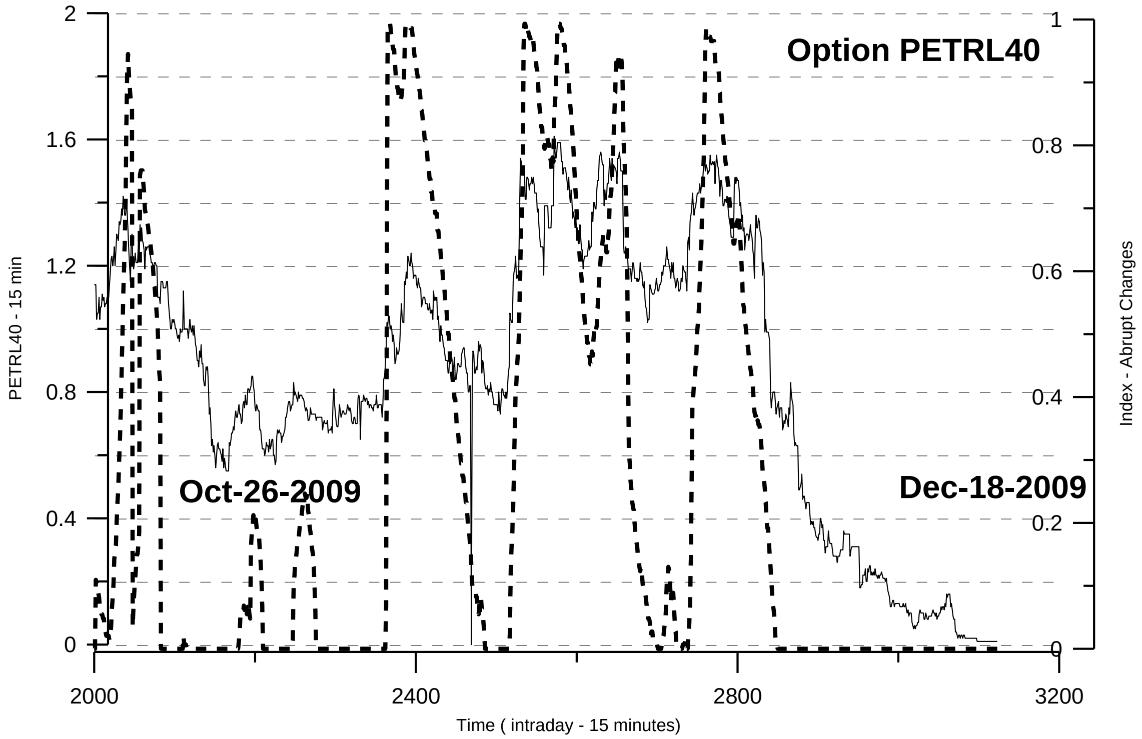

Figure-6: PETRL40 options (left axis) and the proposed index (right axis) in dot-line.

3. Conclusions

This work is concerned with the use of wavelet transform to detect imminent abrupt intraday changes in the stock market. The previous result involved interpreting shades in a two dimensional graph where the values of the wavelet coefficients were coded in gray levels (Caetano & Yoneyama, 2007). Also, the previous index was applicable to daily data (Caetano & Yoneyama, 2009). The new index (again a real number between 0 and 1) was adapted to emit alarm signals in real time, each 15 minutes.

Three case studies were carried out to evaluate the proposed new index (ζ) using Ibovespa data covering 2009 and 2010, as well as options offered by two Brazilian firms. The new index was found to present good capability of monitoring drawdown with low error margins, as verified by statistical data. It was also possible to estimate the maximum waiting time ultil the end of fall, showing that it is possible to use this index to trade during the whole week. However, it is worth stressing that further tests are required, including data from commodities, currency market and others.

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