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Multifractal detrended cross-correlation analysis on gold, crude oil and foreign exchange rate time series

Mayukha Pal [a,b,c], P. Madhusudana Rao [b], P. Manimaran [a,*]

[a] C R Rao Advanced Institute of Mathematics, Statistics and Computer Science, Hyderabad 500046, India
[b] College of Engineering, Jawaharlal Nehru Technological University, Hyderabad-500085, India
[c] India Innovation Center, General Electric Company, Secunderabad-500003, India

HIGHLIGHTS

- We have studied the cross-correlation among four financial time series.
- The recently developed MF-DXA method was used to quantify the cross-correlation.
- The cross-correlation statistic test was used for qualitative analysis of cross-correlation.
- We found the existence of multifractal behavior between all these time series.

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ABSTRACT

We apply the recently developed multifractal detrended cross-correlation analysis method to investigate the cross-correlation behavior and fractal nature between two non-stationary time series. We analyze the daily return price of gold, West Texas Intermediate and Brent crude oil, foreign exchange rate data, over a period of 18 years. The cross correlation has been measured from the Hurst scaling exponents and the singularity spectrum quantitatively. From the results, the existence of multifractal cross-correlation between all of these time series is found. We also found that the cross correlation between gold and oil prices possess uncorrelated behavior and the remaining bivariate time series possess persistent behavior. It was observed for five bivariate series that the cross-correlation exponents are less than the calculated average generalized Hurst exponents (GHE) for $q < 0$ and greater than GHE when $q > 0$ and for one bivariate series the cross-correlation exponent is greater than GHE for all q values.

1. Introduction

A large number of studies have been carried out to understand the fractal characteristics [1,2] and correlation behavior [3] of non-stationary time series which are more complex in nature. Until now various methods have been developed and applied to characterize the correlation behavior on many time series starting from R/S analysis [4–7], detrended fluctuation analysis (DFA) [8–10], detrended moving average method (DMA) [11], multifractal detrended fluctuation analysis (MFDFA) [12], wavelet based fluctuation analysis (WBFA) [13–16], average wavelet coefficient method (AWC) [17], wavelet transform modulus maxima (WTMM) [18] etc. These methods have found wide application in the analysis of correlations and characterization of scaling behavior of time-series data in physiology, finance, and natural sciences

* Corresponding author. Tel.: +91 4023013118; fax: +91 4023013118.
E-mail addresses: pa.manimaran@gmail.com, maran@crraoaimscs.res.in (P. Manimaran).

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[19–29]. Most of these methods not only measure the correlation behavior but also used to study the fractal characteristics of the time series using the Hurst scaling exponent ($0 < H < 1$). This scaling exponent measures the persistent ($H > 0.5$), uncorrelation ($H = 0.5$) and anti-persistent ($H < 0.5$) behavior.

Recently, Podobnik and Stanley introduced an approach detrended cross correlation analysis (DCCA) through which the cross correlation behavior of two non-stationary time series can be investigated [30,31]. Combining the DCCA and MFDFA method Zhou developed a new approach multifractal detrended cross correlation analysis (MF-X-DFA) to characterize the multifractal features of two cross-correlated time series [32]. Similarly, Zhi-Qiang and Zhou developed multifractal detrending moving average cross-correlation analysis method (MF-X-DMA) by integrating DCCA and MFDMA [33]. Using these above mentioned approaches the cross correlation behavior and multifractal characteristics various studies have been carried out in analyzing time series of financial, physical, biological systems [21,34–39]. Among these financial market time series analysis is of great interest for an econo-physicist to uncover the hidden information for forecasting the future price. Crude oil market, one of the main focal points in many countries, has become an increasingly essential topic of concern to governments, enterprises and investors. It is the vital source of energy for the world hence higher crude oil prices drive fuel inflation as crude oil demands are inelastic in nature. Therefore, understanding the dynamics of its price seems to be crucial, since it may allow one to assess the potential impacts of its shocks on other markets and financial assets. Similarly gold price fluctuation and its trading are directly related to market inflation. Historically gold retains its value during times of crisis and is used as a hedge against inflation, deflation or currency devaluation. Hence there is a prospective without empirical evidence in the market that use gold for trading crude oil at the time of inflation though the cross-correlation of crude oil and gold is yet not properly established. Also trading of these commodities is heavily impacted with currency exchange rate fluctuation. So it becomes evident to study and analyze the cross-correlation behavior between gold, crude oil and foreign exchange rate (Forex) time series.

In this paper, we investigate the multifractal cross correlation behavior using the recently developed MF-X-DFA method on gold, West Texas Intermediate (WTI) and Brent crude oil, and Forex (USD/INR) time series. For this purpose, we have analyzed the time series collected over a period of 18 years. Section 2 describes the MF-X-DFA procedure while Section 3 describes the data collection. Section 4 shares the result and discussion and Section 5 provides our conclusions to the study.

2. Methodology

The MF-X-DFA procedure is explained through the following steps. Let us assume that there are two time series $x(i)$ and $y(i)$ where $i = 1, 2, \ldots, N$, where N is the length of the time.

Step 1: Construct the profile of the time series

$$X(i) = \sum_{t=1}^{i} (x(t) - \bar{x}) \tag{1}$$

$$Y(i) = \sum_{t=1}^{i} (y(t) - \bar{y}) \tag{2}$$

where $\bar{x}$ and $\bar{y}$ are the average of the two time series $x(i)$ and $y(i)$.

Step 2: The profile time series $X(i)$ and $Y(i)$ are divided into $N_s = [N/s]$ non-overlapping windows of equal length s. Since the length N is not always a multiple of the considered time scale s hence in order not to discard the section of series, the same procedure is repeated starting from the reverse end of each profile. Thus, $2N_s$ non-overlapping windows are obtained together.

Step 3. The local polynomial trends $X^v(i)$ and $Y^v(i)$ for each segment v (where, $v = 1, 2, 3, \ldots, 2N_s$) are removed by least squares fits of the data, then the detrended covariance is obtained for each segment $v = 1, 2, \ldots, N_s$

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{t} |X((v-1)s + i) - X^v(i)|\,|Y((v-1)s + i) - Y^v(i)|. \tag{3}$$

Similarly, for each segment $v = N_s + 1, N_s + 2, \ldots, 2N_s$.

$$F^2(s, v) = \frac{1}{s} \sum_{i=1}^{t} |X(N - (v - N_s)s + i) - X^v(i)|\,|Y(N - (v - N_s)s + i) - Y^v(i)|. \tag{4}$$

The trends $X^v(i)$ and $Y^v(i)$ are the fitting polynomials with order m in each segment v.

Step 4: The qth order fluctuation function is obtained by squaring and averaging fluctuations over all segments,

$$F_q(s) = \left[\frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2(s, v)]^{q/2} \right]^{1/q}. \tag{5}$$