Physica A 428 (2015) 13–18

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Multifractal analysis of managed and independent float exchange rates

Darko Stošić [a,c], Dusan Stošić [a,c], Tatijana Stošić [b,*], H. Eugene Stanley [c]

[a] Centro de Informática, Universidade Federal de Pernambuco, Av. Luiz Freire s/n, 50670-901, Recife, PE, Brazil

[b] Departamento de Estatística e Informática, Universidade Federal Rural de Pernambuco, Rua Dom Manoel de Medeiros s/n, Dois Irmãos, 52171-900 Recife, PE, Brazil

[c] Center for Polymer Studies and Department of Physics, Boston University, MA 02215, United States

ARTICLE INFO

Article history:
Received 23 December 2014
Available online 11 February 2015

Keywords:
Currency rate
Managed float
Independent float
Market efficiency
Multifractal detrended fluctuation analysis

ABSTRACT

We investigate multifractal properties of daily price changes in currency rates using the multifractal detrended fluctuation analysis (MF-DFA). We analyze managed and independent floating currency rates in eight countries, and determine the changes in multifractal spectrum when transitioning between the two regimes. We find that after the transition from managed to independent float regime the changes in multifractal spectrum (position of maximum and width) indicate an increase in market efficiency. The observed changes are more pronounced for developed countries that have a well established trading market. After shuffling the series, we find that the multifractality is due to both probability density function and long term correlations for managed float regime, while for independent float regime multifractality is in most cases caused by broad probability density function.

1. Introduction

The foreign exchange market (FX) is the world's largest and most liquid financial market. Its huge trading volume, high degree of liquidity, diversification of traders, geographical dispersion, amongst other factors make it uniquely challenging for empirical analysis, forecasting, and model development. The exchange rate regimes followed by governments across the world are crucial determinants of the foreign-exchange market. After World War II, governments adopted the Bretton Woods system where currencies were pegged against the US dollar, which was in turn pegged to gold. Bretton Woods system helped countries avoid inflation and establish credibility of their currencies, but also removed their ability to conduct an independent monetary policy. Consequently, in 1971 the US dollar switched to a floating currency, a move many major governments followed. Floating currencies are made up of two exchange-rate regimes: managed float and independent float. Exchange rates under the independent float regime fluctuate according to the foreign-exchange market, whereas rates under the managed float regime, (also known as dirty float), fluctuate on a daily basis and are influenced by government intervention. Transitions from managed to independent float regimes depend on various economic, political, and market factors. This brings the question how rate transitions affect market efficiency and economic welfare. As an extremely complex system, the FX market represents an ideal polygon for testing the usefulness of various methods including fractals, multifractals, and chaos theory, as tools to quantify market dynamics [1–7]. Multifractal properties as a measure of efficiency of financial markets were extensively studied [8–11], however less is known about efficiency of different exchange

* Corresponding author.
E-mail addresses: ddstosic@bu.edu (D. Stošić), dbstosic@bu.edu (D. Stošić), tastosic@gmail.com (T. Stošić), hes@bu.edu (H.E. Stanley).

http://dx.doi.org/10.1016/j.physa.2015.02.055
0378-4371/

rate regimes [7,12]. In this work we apply the Multifractal Detrended Fluctuation Analysis (MF-DFA) [13] to compare the statistical properties of the Australian Dollar (AUD), Brazilian Real (BRL), Malaysian Ringgit (MYR), New Zealand Dollar (NZD), South Korean Won (KRW), Sweden Krona (SEK), Taiwanese New Dollar (TWD), and Thai Baht (THB) per US Dollar (USD) exchange rate before and after the transition from managed to independent float regimes. We analyze logarithmic returns of daily closing exchange rates and find parameters that describe multifractal spectrum: position of maximum α_0, width of the spectrum W, and skew parameter r. We also apply the MF-DFA analysis on the shuffled series to identify the effects of long term correlations and probability density function. This paper is organized as follows: We first describe the data and present the methodology, then present the results of our analysis, and finally we draw conclusions.

2. Methodology

Multifractal time series are characterized by a hierarchy of scaling exponents corresponding to different scaling behavior of many interwoven subsets of a series [13]. For non-stationary processes several methods have been proposed, such as the wavelet transform modulus maxima (WTMM) method [14], multifractal detrended fluctuation analysis (MF-DFA) [13], and multifractal moving average analysis [15]. In this work we use the MF-DFA method which has been successfully applied in various phenomena such as physiological signals [16], hydrological processes [17], geophysical data [18], forest fires records [19] and financial time series [8,9,11].

The MF-DFA method proceeds as follows [13]: (i) Integrate the original temporal series $x(i)$, $i = 1, \dots, N$ to produce $y(k) = \sum_{i=1}^{k} [x(i) - \langle x \rangle]$, where $\langle x \rangle$ is the mean value of $x(i)$, $k = 1, \dots, N$. (ii) Divide the integrated series $y(k)$ into $N_n = int(N/n)$ non-overlapping segments of length n. Calculate the local trend $y_i(k)$ from a mth order polynomial regression in each segment and subtract it from $y(k)$ to detrend the integrated series. (iii) Calculate the detrended variance of each segment (by subtracting the local trend) and average over all segments to obtain the qth order fluctuation function:

$$F_q(n) = \left\{ \frac{1}{N_n} \sum_{i=1}^{N_n} \left[\frac{1}{n} \sum_{k=(i-1)\,n+1}^{in} [y(k) - y_i(k)]^2 \right]^{q/2} \right\}^{1/q} \tag{1}$$

where q can take any real value except zero. (iv) Repeat this calculation to find the fluctuation function $F_q(n)$ for many different box sizes n. If long-term correlations are present, $F_q(n)$ should increase with n as a power law $F_q(n) \sim n^{h(q)}$, where the scaling exponent $h(q)$ (also called generalized Hurst exponent) is calculated as the slope of the linear regression of $\log F_q(n)$ versus $\log n$.

The generalized Hurst exponent is a decreasing function of q for multifractal time series and constant for monofractal processes. For positive (negative) values of q, exponent $h(q)$ describes the scaling of large (small) fluctuations [13]. The exponent relates to the classical multifractal exponent defined by the standard partition multifractal formalism as $\tau(q) = qh(q) - 1$, where $\tau(q)$ is a linear function for monofractal signals and a nonlinear one for multifractal signals [13]. Multifractal series are also described by the singularity spectrum $f(\alpha)$ through the Legendre transform

$$\alpha(q) = d\tau(q)/dq, \qquad f(\alpha) = q\alpha - \tau(q) \tag{2}$$

where $f(\alpha)$ denotes the fractal dimension of the series subset characterized by the Holder exponent α. For monofractal signals, the singularity spectrum produces a single point in the $f(\alpha)$ plane, whereas multifractal processes yield a humped function [13].

Multifractality in a time series may be caused by: (i) a broad probability density function for the values of the time series; and (ii) different long-term correlations for small and large fluctuations. To determine the type of multifractality one should analyze the corresponding randomly shuffled series. The shuffled series from multifractals of type (ii) exhibit simple random behavior with $h(q) = 0.5$ and $f(\alpha)$ being reduced to a single point, while for multifractals of type (i) the original $h(q)$ dependence (and the width of multifractal spectrum) is not changed. If the shuffled series demonstrates weaker multifractality than the original one, both kinds of multifractality are present [13]. In order to measure the complexity of the series, we fit the singularity spectra to a fourth degree polynomial

$$f(\alpha) = A + B\,(\alpha - \alpha_0) + C\,(\alpha - \alpha_0)^2 + D\,(\alpha - \alpha_0)^3 + E\,(\alpha - \alpha_0)^4 \tag{3}$$

and calculate the multifractal spectrum parameters: position of maximum α_0; width of the spectrum $W = \alpha_{max} - \alpha_{min}$, obtained from extrapolating the fitted curve to zero; and skew parameter $r = (\alpha_{max} - \alpha_0) / (\alpha_0 - \alpha_{min})$ where $r = 1$ for symmetric shapes, $r > 1$ for right-skewed shapes, and $r < 1$ for left-skewed shapes. Roughly speaking, a small value of α_0 suggests the underlying process is more regular in appearance. The width of the spectrum W measures the degree of multifractality in the series (the wider the range of fractal exponents, the richer the structure of the series). The skew parameter r determines which fractal exponents are dominant: fractal exponents that describe the scaling of small fluctuations for right-skewed spectrum, or fractal exponents that describe the scaling of large fluctuations for left-skewed spectrum. These parameters lead to a method of measuring the complexity of the series: a signal with a high value of α_0, a wide range W of fractal exponents, and a right-skewed shape $r > 1$ may be considered more complex than one with opposite characteristics [20].