Chaos, Solitons and Fractals 109 (2018) 195–205

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

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

Does Bitcoin exhibit the same asymmetric multifractal cross-correlations with crude oil, gold and DJIA as the Euro, Great British Pound and Yen?

Gabriel Gajardo[a], Werner D. Kristjanpoller[a,*], Marcel Minutolo[b]

[a] Departamento de Industrias, Universidad Tecnica Federico Santa Maria, Avenida España 1680, Valparaiso, Chile
[b] School of Business, Robert Morris University, 6001 Unviersity Boulevard, Moon Township, PA 15108, USA

ARTICLE INFO

Article history:
Received 6 October 2017
Revised 6 February 2018
Accepted 21 February 2018

Keywords:
Multifractality
Asymmetric cross-correlations
Bitcoin
Exchange rates
Crude oil market
Gold market

ABSTRACT

We applied MF-ADCCA to analyze the presence and asymmetry of the cross-correlations between the major currency rates and Bitcoin, and the Dow Jones Industrial Average (DJIA), gold price and the oil crude market. We find that multifractality exists in every cross-correlation studied, and there is asymmetry in the cross-correlation exponents under different trend of the WTI, Gold and DJIA. Bitcoin shows a greater multifractal spectra than the other currencies on its cross-correlation with the WTI, the Gold and the DJIA. Bitcoin shows a clearly different relationship with commodities and stock market indices which has to be taken into consideration when investing. This has to do with the years this currency has been traded, the characteristics of cryptocurrencies and its gradual adoption by financial organizations, governments and the general public.

1. Introduction

Cryptocurrency is quickly becoming an important aspect of the global financial market. At the time of this writing, Cyrptocurrency Market Capitalization lists the total market capitalization of all cryptocurrency at approximately $144 billion dollars of which Bitcoin accounts for almost half of all the valuation. Bitcoin is currently trading at approximately $4,100 per coin and has a total capitalization of approximately $68 billion USD; a valuation which just five years ago would have been unthinkable. Major financial organizations are taking large positions in cryptocurrencies, retailers are taking coin for payment, and people are sending money abroad. In a 2016 piece, Harwick [1] finds that Bitcoin possesses some attributes that may make it a good complement to currencies of emerging markets. Some of the promise of cryptocurrency comes from the potential to reduce transaction costs, the security in the transaction, and potential reduction in exchange rate risk[2]. However, at present there has been little attention paid to how cryptocurrency behaves.

Given the rising use of the cryptocurrencies, we propose to perform an analysis of the behavior of the value Bitcoin applying fractal theory and comparing it with the behavior of some major global currencies including the Euro, the Great Britain Pound, and the Japanese Yen. In particular, we propose to evaluate the behavior with respect to the presence and asymmetry of cross-correlations between these currencies and three major financial assets: gold, crude oil and the DJIA index.

The current study is motivated by the rise of the interest and potential of cryptocurrency in general and Bitcoin in particular. Analyzing the behavior of Bitcoin with respect to crude oil, gold and the DJIA can be contrasted if its behavior is similar to other currencies. If the results show that there is similarity with respect to other currencies then one may conclude that Bitcoin behaves like any other currency. However, if the results show differences then we might concluded that this an anomaly of the currency or that Bitcoin, and cryptocurrency by extension, does not behave as a currency and may be that its behavior is more similar to another financial asset. In fact, under the Internal Revenue Service (IRS) guidance, crytpocurrency is treated as property for U.S. Federal tax purposes (Notice 2014-21, 2014-16, IRBXXX). Even if the results are dissimilar one could conclude that we are facing a financial bubble or irrational exuberance.

Recent movements in the exchange rate between Bitcoin and the U.S. Dollar highlight the importance of understanding the behavior of the asset. On December 17, 2017 the exchange rate between Bitcoin and the USD broke the $20,000 mark and in the same day closed at just above $19,000. In the month and a half since the all-time high, the rate has dropped back down to a low

* Corresponding author.
E-mail address: werner.kristjanpoller@usm.cl (W.D. Kristjanpoller).

https://doi.org/10.1016/j.chaos.2018.02.029
0960-0779/

closing price of $7,100. The movement suggests that cryptocurrencies remain a speculators market and perhaps we have just witnessed the largest bubble in Bitcoin to date. Hence, the need to develop a better understanding of this instrument.

Assuming that cryptocurrency in general, and Bitcoin in particular, one needs to apply a model that captures the potential nonlinearity of the instrument. Traditional techniques such as Ordinary Least Squares is limited in its ability to capture complex relationships between data. Cheung et al. [3] applied an augmented Dickey–Fuller test and found the presence of a number of short-lived bubbles and three large bubbles in their analysis of Bitcoin. Their approach was selected to test for explosive behavior in a given time series. Hence, a different approach that has the potential to capture the complexity and is more robust is sought. To this end, we propose to apply fractal analysis to the time series.

One of the most widely used tests to determine the fractal dimension of a given time series is the Rescaled Range Analysis (R/S), introduced by Hurst [4,5]. One of the main benefits of the R/S analysis is that it is robust in that its behavior is related only by the long-term persistence dependence being able to detect non-periodic cycles even if they have a length greater than the analyzed sample period. Additionally, R/S is able to detect long-term correlations in random processes. Mandelbrot and Wallis [6] using R/S found that many natural phenomena are not independent random processes; and, giving an interpretation to the exponent of Hurst H there is significant long-term correlation.

One could use other approaches; however, there are limitations to others that fractal analysis overcomes. For instance, some limitations of traditional models, such as Fourier transform and spectral analysis, fail to qualify scaling behaviors. Peng et al. [7] developed the Fluctuation Analysis (FA) method and then the Detrended Fluctuation Analysis (DFA) method [8]. Because the mono-fractal scaling behavior cannot fully describe the uneven multi-fractal characteristics of the time series and signals, it is necessary to develop the Multi-Fractal Detrended Fluctuation Analysis (MF-DFA) [9,10]. The MF-DFA method has been applied in many fields [11–17]. Particularly in the field of finance MF-DFA has been applied to analyze stock market [18–28], exchange rates [29–39], interest rates [40], market efficiency [41–46], risk market valuation [47,48], financial crisis [49,50], investment strategies [51], gold market [52–55], crude oil market [56–59], and the future market [60–62].

Since the behavior of financial assets may contain components of trends and asymmetry in the reaction to different impacts Alvarez-Ramirez et al. [63] introduced the asymmetric DFA (A-DFA) to analyze asymmetric correlations in the scaling behavior of the time series. Cao et al. [64] further extended the DFA (A-DFA) with the proposition of the asymmetric multi-fractal detrended fluctuation analysis (A-MFDFA). Further, Zhang et al. [65] introduced the asymmetric multi-fractal detrending moving average analysis (A-MFDMA). Recently, Lee et al. [66] used A-MFDMA to analyze U.S. stock market indexes while Gajardo and Kristjanpoller [67] applied the cross-correlation version of the A-MFDFA, the A-MFDCCA, to study the Latin American stock markets and their relationship with the oil market.

Analyzing the behavior of Bitcoin with respect to crude oil, gold and DJIA, one can be contrasted if its behavior to determine its similarity to the major currencies. If the results show that there is similarity with the other currencies a conclusion could be that Bitcoin behaves like any other currency; but, if the results show differences it can be concluded that this is an anomaly of a currency or that Bitcoin does not behave as a currency and may be that its behavior is more similar to another financial asset. Even if the results are dissimilar one might conclude that we are facing a financial bubble or irrational exuberance. This is the first study of Bitcoin's multifractal properties. The comparison of the multifractal and asymmetric behavior of the currencies is carried out with respect to three major financial assets, the price of gold, the price of crude oil and the DJIA stock index.

The remainder of this paper is organized as follows. Section 2 describes the method used, Section 3 describes the data used in the analysis. Section 4 provides the results obtained. In the final section of the manuscript, we present our conclusions and recommendations.

2. Multifractal asymmetric detrended cross-Correlation analysis method

Two time series x_i and y_i, $i = 1, \ldots, N$, N is the length of the series. The following steps summarizes the approach [67].

First: Construct the profile

$$X(i) = \sum_{t=1}^{i} (x_t - \bar{x}), \quad Y(i) = \sum_{t=1}^{i} (y_t - \bar{y}), \quad i = 1, \ldots, N \tag{1}$$

Where $\bar{x}$ and $\bar{y}$ represent the average of the series in the whole period. Second: $X(i)$ and $Y(i)$ are separated into $N_s \equiv [N/s]$ non-overlapping windows of equal length s. Since the length of the series N is not necessarily a multiple of the time scale s, some part of the profile can remain at the end. In order to not discard this part, the same procedure is applied starting from the end of the series. This means that we obtain $2N_s$ segments. Third: The trends, $X^{\nu}(i)$ and $Y^{\nu}(i)$ for each one of the $2N_s$ segments are estimated with a linear regression as: $X^{\nu}(i) = a_{X^{\nu}} + b_{X^{\nu}} \cdot i$ and $Y^{\nu}(i) = a_{Y^{\nu}} + b_{Y^{\nu}} \cdot i$. This precedes the determination of the detrended covariance, calculated as follows

$$F(\nu, s) = \frac{1}{s} \sum_{i=1}^{s} |X[(\nu-1)s + i] - X^{\nu}(i)| \cdot |Y[(\nu-1)s + i] - Y^{\nu}(i)| \tag{2}$$

for each segment ν, $\nu = 1, \ldots, N_s$ and

$$F(\nu, s) = \frac{1}{s} \sum_{i=1}^{s} |X[N - (\nu - N_s)s + i] - X^{\nu}(i)| \cdot |Y[N - (\nu - N_s)s + i] - Y^{\nu}(i)| \tag{3}$$

for each segment ν, $\nu = N_s + 1, \ldots, 2N_s$.

Fourth: The qth order of the fluctuation function is obtained as follows for the different behavior of the trends in time series x_t

$$F_q^{+}(s) = \left(\frac{1}{M^{+}} \sum_{\nu=1}^{2N_s} \frac{sign(b_{X^{\nu}}) + 1}{2} [F(\nu, s)]^{q/2} \right)^{1/q} \tag{4}$$

$$F_q^{-}(s) = \left(\frac{1}{M^{-}} \sum_{\nu=1}^{2N_s} \frac{-[sign(b_{X^{\nu}}) - 1]}{2} [F(\nu, s)]^{q/2} \right)^{1/q} \tag{5}$$

when $q \neq 0$, and

$$F_0^{+}(s) = exp\left(\frac{1}{2M^{+}} \sum_{\nu=1}^{2N_s} \frac{sign(b_{X^{\nu}}) + 1}{2} [F(\nu, s)]^{q/2} \right)^{1/q} \tag{6}$$

$$F_0^{-}(s) = exp\left(\frac{1}{2M^{-}} \sum_{\nu=1}^{2N_s} \frac{-[sign(b_{X^{\nu}}) - 1]}{2} [F(\nu, s)]^{q/2} \right)^{1/q} \tag{7}$$

for $q = 0$. $M^{+} = \sum_{\nu=1}^{2N_s} \frac{sign(b_{X^{\nu}})+1}{2}$ and $M^{-} = \sum_{\nu=1}^{2N_s} \frac{-[sign(b_{X^{\nu}})-1]}{2}$ are the number of subtime series with positive and negative trends. We assume $b_{X^{\nu}} \neq 0$ for all $\nu = 1, \ldots, 2N_s$, such that $M^{+} + M^{-} = 2N_s$.