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Testing for Long-memory and Chaos in the Returns of Currency Exchange-traded Notes (ETNs)

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Abstract

The study uses autoregressive fractionally integrated moving average – fractionally integrated generalized autoregressive conditional heteroskedasticity (ARFIMA-FIGARCH) models and chaos effects to determine nonlinearity properties present on currency ETN returns. The results find that the volatilities of currency ETNs have long-memory, non-stationarity and non-invertibility properties. These findings make the research conclude that mean reversion is a possibility and that the efficient market hypothesis of Fama (1970) became ungrounded on these investment instruments. For the chaos effect, the BDS test finds that ETN returns and ARMA residuals also exhibit random processes, making conventional linear methodologies not appropriate for their analysis. The R/S analysis shows that currency ETN returns, ARMA and GARCH residuals have chaotic properties and are trend-reinforcing series. On the other hand, the correlation dimension analyses further confirmed that the utilized time-series have deterministic chaos properties. Thus, investors trying to predict returns and volatility of currency ETNs would fail to produce accurate findings because of their unstable structures, confirming their non-linear properties.

JEL classification numbers: G10, G15
Keywords: Currency ETNs, Long-memory Properties, ARFIMA-FIGARCH, Chaos Effects.

1 Introduction

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Economic theory offered explanations that irregular tendencies might be attributed to the existence of nonlinear properties of some investment instruments. The straightforward solutions offered by linear models are often inadequate to the growing complexities of financial time-series. Most of the times, large price changes are not followed by relatively huge movements and at times even small reactions trigger great changes, leading to a solid conclusion that market volatilities are not constant over time. Financial time-series exhibits irregular behavior wherein a process response is not proportional to the stimulus given making the mathematics behind it difficult to comprehend.

This paper determines the application of two nonlinear models, namely long-memory and chaos to capture nonlinear characteristics of currency ETN returns. These two models, as revealed by Wei and Leuthold (1998) and Panas (2001) were able to capture long memory and chaos in agricultural futures and metal futures prices, respectively. Extant literatures recently have shown the presence of nonlinearity in investment instruments (e.g., Antoniou and Vorlow, 2005; Das and Das, 2007; Korkmaz et al., 2009; and Mariani et al., 2009), but because of the recent genesis of ETNs, nonlinear dynamics is not yet applied on its returns. Given the growing number of investments being put on these financial instruments, studying their nonlinear tendencies through long-memory and chaos is timely.

Smith and Small (2010) defines ETNs[1] as senior, unsecured debt securities issued by an investment bank which promises a rate of return that is based to the change in value of a tracked index. These instruments are traded daily on stock exchanges (i.e., AMEX and NYSE), and can also be shorted or bought as a long position. Based on Wright et al. (2009), ETNs are comparable to zero-coupon bonds that are with medium- to long-term maturities and sold in zero-denominations. They can also be redeemed early and have variable interest rates. ETNs have no tracking errors, because their returns closely imitate that of an underlying index; and provide investors a tax advantage related to the holding period. Small investors can use ETNs to access difficult to reach type of investments like commodity futures or a particular type of investing strategies.

Currency ETNs are designed to give investors exposure to total returns of a single foreign currency index or a basket of currencies index. For example, the iPath EUR/USD Exchange rate ETN (Ticker: ERO) tracks the performance of the Euro/US dollar exchange rate which is a foreign exchange spot rate that measures the relative values of the Euro and US dollar. The exchange rate increases when the euro appreciates against the US dollar and decreases if the euro depreciates. ETNs like ERO, are attractive to investors trying to hedge their exposure to the dollar or even looking an opportunity to bet against the dollar, because their index values are also a possible avenue for diversification.

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[1] For a detailed discussion on ETNs please see the papers of Smith and Small (2010), Wright et al. (2010) and Washer and Jorgensen (2011)

This paper is a pioneer in applying ARFIMA-FIGARCH models in examining the long-memory, and in utilizing chaos effects in determining chaotic tendencies of currency ETN returns and volatilities. The purpose of this study is to provide additional evidence of nonlinearities in economic time-series from the perspective of ETNs. To the best of our knowledge no research yet has been done to these new investment instruments. The research is motivated by the fact that providing new understanding in the non-linear properties of currency ETNs creates considerable amount of knowledge for both academicians and researchers. The results can also provide the academic community potential avenues for research. Also, proper modeling of this new type of investment instruments through nonlinearities; and checking the existence of short, intermediate and long memories, and chaotic properties of ETNs can yield better results that will benefit the investing community in creating potential opportunity to create profit.

The short findings of this paper found the returns of currency ETNs non-stationarity and non-invertibility properties. This makes the research conclude that the efficient market hypothesis of Fama (1970) stands on solid grounds for the time-series utilized and mean reversion is not present. The BDS test found that ETN returns and ARMA residuals exhibit random processes. The R/S analysis showed that currency ETN returns, ARMA and GARCH residuals have chaotic properties and are trend-reinforcing. The correlation dimension analyses further confirmed that the time-series utilized have deterministic chaos properties. Thus, investors trying to predict returns and volatility of currency ETNs would fail to produce accurate findings.

The research is structured as follows. Section 2 narrates related studies, Section 3 explains the data and methodology of ARFIMA-FIGARCH, BDS test, R/S analysis and correlation dimension; Section 4 interprets the empirical findings; and Section 5 provides the conclusion.

2 Related Literature

This part gives a narration of researches proving the existence of non-linear dynamics in the returns of foreign exchange markets. These literatures address two main topics: (1) reviews studies that established long-memory and mean reversion in exchange rates, and (2) covers literatures that explained the chaotic tendencies of currency markets.

Analyzing econometric time-series in a nonlinear framework, according to Panas (2001), have three primary reasons. The author explained that nonlinearities communicate information about the inherent structure of the data series. These nonlinearities then offer insight into the nature of the process that dominates the structure. And through these methods, it would be easy to distinguish between the stochastic and chaotic properties of the time-series, which is very difficult or even impossible to determine using linear models.

Long-memory dynamics in the literature have been applied to several financial instruments and foreign exchange rates. Kang and Yoon (2007), Korkmaz et al. (2009), and Tan and Khan (2010) established the fact that long memory properties can exist in both returns and volatilities in the stock markets, while Choi and Hammoudeh (2009) found evidence of long memory in spot and futures returns and volatilities for oil-related products. Hafner and Herwartz (2006) in the study of the currency market were able to track the effect of shocks on volatility through time in the time-series of franc/US dollar and mark/US dollar. Beine et al. (2002) modeled exchange rates using ARFIMA-FIGARCH and found that the persistence of volatility shocks in the pound, mark, franc and yen share similar patterns. On the other hand, Nouira et al. (2004) used ARFIMA model and showed that by isolating the unstable unconditional variance, long-memory was detected on the exchange rate of euro/US dollar returns.

Related forecasting studies in ETPs are present with the paper of Mariani et al. (2009), when they demonstrated that the degree of long memory effects of SPDR S&P 500 ETF (Ticker: SPY) and SPDR Dow Jones Industrial Average ETF (Ticker: DIA) is virtually the same as their tracked indices, showing the efficiency of ETFs' mimicking the behavior. In a recent study, Yang et al. (2010) used GARCH model to determine return predictability of eighteen stock index ETFs. Their evidence showed that six ETFs have predictable structures. Rompotis (2011) also examined the performance persistence of iShares ETFs and also tried to determine their predictability. The study found that ETF returns are superior than the S&P 500 Index in the short-run and also concluded that ETF performances are somehow predictable through a dummy regression analysis.

Chaotic tendencies of variables, on the other hand, have also been detected from financial instruments and currency markets. The seminal work of Hsieh (1991) provided a comprehensive discussion in the presence of chaos in financial markets and also agreed that financial time-series may have chaotic behavior. Blank (1991) and Kyrtsou et al. (2004) reported nonlinear dynamics in futures prices, and also found that short-term forecasting models may be improved by chaotic factors. Panas and Ninni (2000) showed that the price sequence of oil markets contains non-linear dynamics and that ARCH-GARCH models and chaos effects can best capture these tendencies. In a latter study, Moshiri and Faezeh (2006) stated that crude oil futures prices have complicated nonlinear dynamic patterns. Furthermore, Panas (2001) applied both long-memory and chaos effects to London metal prices, and found that aluminum can be modeled by the long-memory process and tin prices supported chaos.

The significance of chaos in the foreign exchange markets according to Yudin (2008) is that investors would be able to find powerful trends that can help in predicting the currency market. There are however mixed literatures in determining chaos in foreign exchange markets. For example, Das and Das (2007) revealed that foreign exchange markets exhibited deterministic chaos nonlinear processes. Few results were found by Serletis and Gogas (1997) when they utilized chaos effects to determine the tendencies of seven Eastern European countries. They only found two out of seven exchange rates consistent with chaos. In a recent study of Adrangi et al. (2010) utilizing correlation dimension and BDS in the US dollar, Canadian dollar, Japanese yen and Swiss franc exchange rates, they only found nonlinear dependence in their data and not chaos properties. But Jin (2005) argued that the absence of chaotic tendencies in foreign exchange markets in a particular time can change depending on the degree of competition in the market; and may be even affected by transmission of volatility from other foreign exchange markets (Cai et al., 2008 and Bubak et al., 2011).

We can conclude from the above literatures, nonlinear properties, particularly long-memory and chaos exists in the financial markets, foreign exchange markets and other financial instruments. However, chaotic tendencies are yet to be established in ETPs. These evidences make us believe that currency ETNs are a good avenue in establishing long-memory, especially chaotic properties since its recent genesis lacks the study of its further characterization.

3 Data and Methodology

This paper utilizes daily closing prices of currency ETNs obtained from the Google Finance Website. The research period begins at the varying inception dates of the ETNs. As of February 5, 2012, About.com website listed 188 ETNs. The data was limited to five because most ETNs are in their early stages of inception and some are not actively traded having numerous presence of zero volumes and zero returns. Currency ETNs featured in this study have almost $17.5 billion in market capitalization. This considerable amount of investment in this security inspired this paper to examine its long memory properties and chaotic tendencies that may have significant economic value. These ETNs were chosen because they link their returns on specific type of foreign exchange market and are actively traded.

The autoregressive fractionally integrated moving average (ARFIMA) model is a parametric approach in econometric time-series that examines long-memory characteristics (Granger and Joyeux, 1980; and Hosking, 1981). This model allows the difference parameter to be a non-integer and considers the fractionally integrated process in the conditional mean, unlike the autoregressive integrated moving average (ARIMA) model proposed by Box and Jenkins (1976) where the difference parameter only takes an integer value. While the fractionally integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model as by Baillie et al. (1996) captures long memory in return volatility, the process gives more flexibility in modeling the conditional variance. On the other hand, chaos offers an assumption that at least part of underlying process is nonlinear, and also evaluates the determinism of the process. Hsieh (1991) defines chaos as a nonlinear deterministic series that appears to be random in nature and cannot be identified as nonlinear deterministic system or a nonlinear stochastic system. This means that the dynamics of chaotic process can be misconstrued as a random process by conventional a linear econometric method, that is why appropriate modeling is necessary to come up with accurate findings.

3.1. Long memory properties

The ARFIMA (p,d,q) model is used to examine the long-memory characteristics (Granger and Joyeux, 1980; and Hosking, 1981) of ETNs. This econometric model permits the difference parameter to be a non-integer and considers the fractionally integrated process $I(d)$ in the conditional mean. The ARFIMA model, as defined by Korkmaz et al. (2009) can be illustrated as:

$$\Phi(L)(1-L)^d Y_t = \Theta(L)\varepsilon_t, \varepsilon_t \sim (0,\sigma_\varepsilon^2), \qquad (1)$$

where

d is the fractional integration real number parameter;

L is the lag operator; and

ε_t is a white noise residual.

This equation satisfies both the assumptions of stationarity and invariability conditions.

The fractional differencing lag operator $(1-L)^d$ can be further illustrated by using the expanded equation below:

$$(1-L)^d = 1 - dL + \frac{d(d-1)}{2!}L^2 - \frac{d(d-1)(d-2)}{3!}L^3 + ... \qquad (2)$$

Based on Hosking (1981), and as applied by Kang and Yoon (2007) and Korkmaz et al. (2009), when $-0.5 < d < 0.5$, the series is stationary, wherein the effect of market shocks to ε_t decays at a gradual rate to zero. When *d = 0*, the series has short memory and the effect of shocks to ε_t decays geometrically. When *d = 1*, there is the presence of a unit root process.

Furthermore, there is a long memory or positive dependence among distant observations when *0 < d < 0.5*. Also, the series has intermediate memory or antipersistence when *-0.5 < d < 0* (Baillie, 1996). The series is non-stationary when $d \geq 0.5$. While the series is stationary when $d \leq -0.5$, but considered a non-invertible process, which means that the series cannot be determined by any autoregressive model.

The FIGARCH $(p,\bar{d},q)$ model captures long memory in return volatility (Baillie et al., 1996). The model is more flexible in modeling the conditional variance, capturing both the covariance stationary GARCH for $\bar{d}=0$, and the non-stationary IGARCH for $\bar{d}=1$. The FIGARCH model can be illustrated as:

$$\phi(L)(1-L)^{\bar{d}}\varepsilon_t^2 = \omega + [1-\beta(L)]v_t, \qquad (3)$$

where

v_t is the innovation for the conditional variance, and $\phi(L)$ and $[1-\beta(L)]$

have roots that lie outside of the unit root circle. The differencing parameter d dictates the long-memory property of the volatility if $0 \leq d \leq 1$.

3.2. Chaos methodologies

According to Peters (1994), the existence of a fractal dimension and sensitive dependence on initial conditions are the two necessary requirements in order for a structure to be chaotic. Figure 1 illustrates a Mandelbrot Set wherein a figure of a fractal is shown. A time series with high affinity will show that no matter how large the magnification of a fractal, the shape of the Mandelbrot Set will still be similar to the original one. As shown in the magnified Figure 2, it indicates that a system is similar in affinity with its entirety. This research utilizes three different approaches in testing if the underlying time series data of five currency ETNs have chaotic tendencies. The detailed methodologies are as follows:

3.2.1. Brock, Dechert, and Scheinkman test

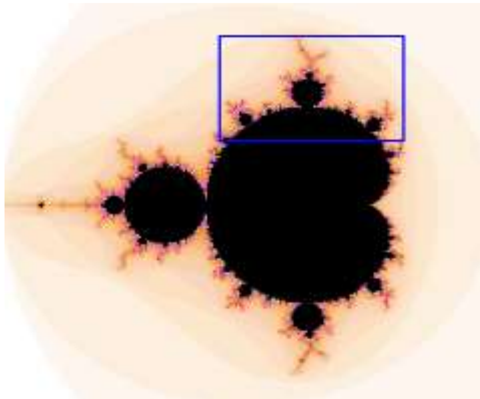
The BDS test, devised by Brock et al. (1996) is a powerful test in separating random series from deterministic chaos or from nonlinear stochastic series. Chaos as defined by Hsieh (1991) is a nonlinear deterministic series that seems random in nature and cannot be identified as nonlinear deterministic system or a nonlinear stochastic system. The BDS statistic calculates statistical significance of the correlation dimension and determines nonlinear dependence. When Opong et al. (1999) applied this test to FTSE stock index returns, they found that the series is not random because of detected frequent showing of patterns. However, according to Hsieh (1991), the BDS test has a low power against autoregressive (AR) and ARCH models, and before proceeding with the test; the observations are pre-filtered with a linear filter such as ARMA (or ARIMA) and a nonlinear filter such as GARCH.

The BDS test uses a statistic based on the correlation integral which is computed as:

$$C_N(l,T) = \frac{2}{T_N(T_N-1)} \sum_{t<s} I_l(x_t^N, x_s^N), \tag{4}$$

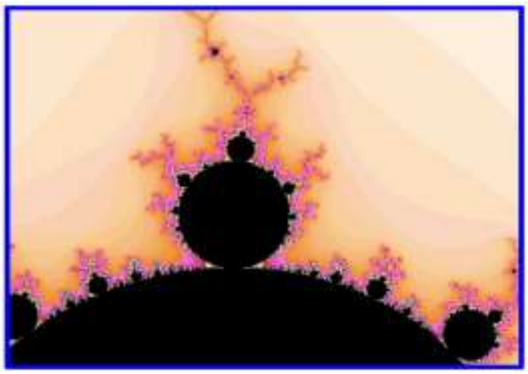
where $T_N = T - N + 1$.

The correlation integral is based on a given sequence $\{x_t : t = 1,...,T\}$ of observations which are independent and identically distributed (*iid*), and N-dimensional vectors $\left[x_t^N = (x_t, x_{t+1},...x_{t+N-1})\right]$, called the "N-histories".



Source: Based on the illustration of Aros fractals software

Figure 1: Mandelbrot set fractals



Source: Based on the illustration of Aros fractals software

Figure 2: Magnified version of the Mandelbrot set fractals

Brock et al. (1996) illustrated that the null hypothesis $\{x_t\}$ is *iid* with a non-degenerative density *F*, $C_N(l,T) \to C_1(l)^N$ with probability of one, as $T \to \infty$, for any fixed *N* and *l.* Also, the author proposed that $\sqrt{T}\left[C_N(l,T) - C_1(l,T)^N\right]$ has a normal distribution with zero mean and variance:

$$\sigma_N^2(l) = 4\left[K^N + 2\sum_{j=1}^{N-1} K^{N-1}C^{2j} + (N-1)^2 C^{2N} - N^2 K C^{2N-2}\right], \tag{5}$$

where

$$C = C(l) = \int [F(z+1) - F(z-1)] dF(z), K = K(l) = \iint [F(z+1) - F(z-1)]^2 dF(z) .$$

Furthermore, $C_1(l,T)$ is a consistent estimate of *C(l)*, and

$$K(l,T) = \frac{6}{T_N(T_N - 1)(T_N - 2)} \sum_{t<s<r} I_l(x_t, x_s) I_l(x_s, x_r) . \tag{6}$$

Eq. (6) is also a consistent estimate of K*(l).* Therefore, $\sigma_N(l)$ can be estimated consistently by $\sigma_N(l,T)$, which $C_1(l,T)$ and $K_1(l,T)$ can replace $C(l)$ and $K(l)$ in the equation. The BDS statistic which follows a normal distribution can be illustrated below:

$$w_N(l,T) = \sqrt{T}\left[C_N(l,T) - C_1(l,T)^N\right] / \sigma_N(l,T) , \tag{7}$$

where $\sigma_N(l,T)$ is the standard deviation of the correlation integrals.

3.2.2. Rescaled Range analysis: Hurst exponent

R/S analysis is a test defined by the range and standard deviation (R/S statistic) or the so-called reschaled range. Hurst (1951) first developed the rescaled range procedure, with improvements made by Mandelbrot and Wallis (1969), and Wallis and Matalas (1970) The major shortcoming of the traditional rescaled range (R/S) is that it can identify range dependencies, without discrimination between short and long dependencies (Lo, 1991). And the modified R/S analysis was able to remove short-term dependencies and also able to detect long term dependencies. Peters (1994) and Opong et al. (1999) showed the procedures on how to perform the R/S analysis. Each of the ETNs under study is initially transformed into logarithmic return given by:

$$S_t = \ln(P_t / P_{+-1}) , \tag{8}$$

where S_t = logarithmic returns at time *t*, and P_t =price at time *t*. The S_t series is pre-whitened to reduce the effect of linear dependency and non-stationarity by adopting an AR(1) model to S_t which is shown as follows:

$$S_t = \alpha + \beta S_{t-1} + \varepsilon_t , \tag{9}$$

where S_{t-1} is the logarithmic return at time period *t-1*. α and β represent the parameters to be estimated and ε_t is the residual.

Based on the application of Opong et al. (1999) and Peters (1994), the time period is separated into *A* adjacent sub-periods of length *n,* such that $A \times n = N$, where *N* denotes the extent of the series N_t. Each sub-period is labeled I_a, *a*=1,2,3,…,*A*. The elements contained in I_a is marked $N_{k,a}$, *k*=1,2,3,…,*n*. The average value e_a for each I_a of length *n* is

$$e_a = \left(\frac{1}{n}\right) \times \sum_{k=1}^{n} N_{k,a} \ . \qquad (10)$$

The range R_{I_a} is the difference between the maximum and minimum value $X_{k,a}$, within each sub-period I_a is

$$R_{I_a} = \max(X_{k,a}) - \min(X_{k,a}), \text{ where } 1 \le k \le n,\ 1 \le a \le A, \qquad (11)$$

where

$X_{k,a} = \sum_{i=1}^{k} (N_{i,a} - e_a)$, k=1,2,3,…,n represents the time series for each sub-period of departures from the mean value. R/S analysis requires the R_{I_a} to be normalized by dividing by the sample standard deviation S_{I_a} equivalent to it and is calculated as follows:

$$S_{I_a} = \left[\frac{1}{n} \times \sum_{k=1}^{n} (N_{k,a} - e_a)^2\right]^{0.50} . \qquad (12)$$

The average R/S values for length *n* is computed as:

$$\left(\frac{R}{S}\right)_n = \left(\frac{1}{A}\right) \times \sum_{a=1}^{A} (R_{I_a} / S_{I_a}). \qquad (13)$$

The application of an OLS regression with log(*n*) as the independent variable and $\log(R/S)$ as the dependent variable is the last step in the analysis. The Hurst exponent, *H* is derived from the slope obtained from the regression. The three values of the *H* exponent would be: $H = 0.5$, which denotes that the series follows a random walk; $0 \le H < 0.5$, which stands for an anti-persistent series; and $0.5 < H < 1$, which means that the series is a persistent, or is a trend-reinforcing series. The R/S analysis is appraised by computing the expected values of the R/S statistics which is shown as:

$$E(R/S) = \left[\left(\frac{n-0.5}{n}\right) \times \left(\frac{n \times \pi}{2}\right)\right]^{-0.50} \times \sum_{r=1}^{n-1} \sqrt{\frac{(n-r)}{r}} \ . \qquad (14)$$

The expected Hurst exponent is derived from the slope of the regression of $E(\log(R/S)_n$ on log(*n*). The variance of the Hurst exponent is shown as:

$$Var(H)n = \frac{1}{T}, \qquad (15)$$

where *T* denotes the total number of observations in the series.

3.2.3. Correlation Dimension Analysis

Correlation dimension (CD) introduced by Grassberger and Procaccia (1983), provides a diagnostic process in distinguishing deterministic and stochastic time series $\{x_t\}$. It determines the degree of complexity of a time-series, which can be a sign of having chaos. Kyrtsou and Terraza (2002) made an empirical study and showed evidence based on correlation dimension (CD) that the French CAC40 returns can be either generated through a noisy chaotic or a pure random process. Based on the studies of Grassberger and Procaccia (1983), and Hsieh (1991), the analysis initially requires the filtering of the observations throuth the ARMA and GARCH processe from autocorrelation and conditional heteroscedasticity, respectively which can negatively affect some tests for chaos.

Next step is to create *n*-histories of the filtered data, which are illustrated as follows:

1-history: $x_t^1 = x_t$, (16)

2-history: $x_t^2 = (x_{t-1,} x_t)$, (17)

:

n-history: $x_t^n = (x_{t-n+1,\ldots,} x_t)$. (18)

where *n*-history represents a particular point in the *n*-dimensional space.

The correlation integral is then calculated, which is utilized by Grassberger and Procaccia (1983) and define the correlation dimension as follows:

$$C_n(\varepsilon) = \lim_{T\to\infty} \#\{(t,s), 0 < t, s, < T : \|x_t^n - x_s^n\| < \varepsilon\} / T^2, \qquad (19)$$

where # represents the number of points in the set, and $\|\ \|$ denotes the sup- or max- norm. Thus, the correlation integral $C_n(\varepsilon)$ is defined as the fraction of pairs (x_s^n, x_t^n), which are close to each other, based on :

$$\max_{i=0,\ldots n-1}\{|x_{s-i} - x_{t-i}|\} < \varepsilon\ . \qquad (20)$$

The final step requires calculating the slope of $\log C_n(\varepsilon)$ on $\log\varepsilon$ for small values of ε with the equation below:

$$v_n = \lim_{\varepsilon\to 0} \log C_n(\varepsilon) / \log\varepsilon\ . \qquad (21)$$

The series is consistent with chaotic behavior if the correlation dimension (v_n) does not increase with *n*.

4 Empirical Results

Table 1 shows that currency ETN returns mostly have minimal losses and gains. The highest positive return that we could have on our sample is just 2.1% from the URR ETN, and the lowest negative return is 0.3% from the DRR ETN. These two ETNs also have the highest volatility in the samples. Following the Modern Portfolio Theory of Markowitz (1952), we can tell that with the greater dispersion of these ETN returns, the higher their risk which may lead to higher gains and higher losses. The lowest positive return and lowest volatility is ICI ETN. Most of the samples are negatively skewed except for DRR and ICI and the kurtosis coefficients have leptokurtic distributions. The Jarque-Bera statistic for residual normality shows that the ETN returns are under a non-normal distribution assumption. All ETN samples have no serial correlation. The minimum value of the Akaike Information Criterion (AIC) is used to identify the orders of ARFIMA and FIGARCH models. Enders (2004) discussed that the AIC has more power in small sample sizes. This paper used the Lagrange Multiplier Test (ARCH-LM) to test the ARCH effect. We can apply GARCH models in the chosen dataset, because the null hypothesis for all ETN samples was rejected.

4.1. Long memory property results

Table 2 illustrates the results for both ARFIMA and ARFIMA-FIGARCH models. ARFIMA model identified two significant results. The returns of CNY and ICI ETNs exhibited a non-invertible stationary process, which means that it cannot be represented by any autoregressive process. For the return volatility outcome proposed by Baillie et al. (1996) for the FIGARCH model, ERO ETN sample showed non-stationarity and is also difficult to model. However, this study considers the volatility structure of the remaining DRR, CNY, ICI and URR returns to be exhibiting long-memory processes in their volatility structures, similar to what Kang and Yoon (2007) and Tan and Khan (2010) observed in studying the Korean and Malaysian stock market returns, respectively. These make the study conclude that the efficient market hypothesis of Fama (1970) is not consistent with this type of investment instruments and that mean reversion[1] is also possible because of the presence of long memory properties, which also is consistent to the earlier conclusion of Rompotis (2011). Thus, fund managers and investors trying to model and forecast the following ETNs would have the possibility of having extra returns, because their structures are predictable. The pricing efficiency of ETPs is earlier proven by the researches of Kayali (2007) and Zhou (2010) in their studies of actively traded ETFs in Pakistan and US, respectively; and of Wright et al. (2010) in their introduction of ETN paper, and this study found evidences saying the opposite.

The initial results of ARFIMA-FIGARCH models provided a good starting

[1] Mean reversion is the tendency of prices and returns to eventually or in the long-run move back towards the average rate in the market (Henry and Olekalns, 2002).

point to characterize currency ETN returns. This paper conducted further testing to provide additional characterization on the inherent structure of currency ETN returns and what causes this deterministic behavior. This study found another set of answers on the chaos process to support this claim. This research initially did filtering of the data and Table 3 shows that the alternative of no unit roots is not rejected in all ETN returns through the Augmented Dickey-Fuller (ADF) unit-root test. To determine optimal lags for ETN returns, ARMA residuals and GARCH residuals models, the minimum value of the Akaike Information Criterion (AIC) was applied. The findings also presented that the null hypothesis of no serial correlation cannot be rejected for

Table 1: The Sample Size and Period of Currency ETNs

Currency ETNs	Start of Data	Obs.	Mean	Std. Dev.	Skew.	Kurt.	J-Bera	LM test
iPath EUR/USD Exchange Rate ETN (ERO)	May 11 2007	925	-0.002	0.430	-0.144	20.310	11.589***	9.157
Market Vectors Double Short Euro ETN (DRR)	May 8, 2008	849	-0.003	0.732	0.219	1.070	47.321***	13.051
Market Vectors Renminbi/USD ETN (CNY)	Mar. 17, 2008	833	-0.001	0.243	-0.268	54.818	1.043***	10.969
iPath Optimized Currency Carry ETN (ICI)	Oct. 2, 2008	717	0.003	0.216	0.255	0.977	36.316***	9.117
Market Vectors Double Long Euro ETN (URR)	May 8, 2008	641	0.021	0.965	-0.133	1.948	103.25***	12.556

Source: Yahoo Finance – various inception dates up to September 30, 2011; http://www.yahoo.com/finance.

Table 2: Summary Statistics of ARFIMA and ARFIMA-FIGARCH models

Green ETFs	ARFIMA				ARFIMA-FIGARCH			
	model	d-coeff.	AIC	ARCH-LM	d-coeff.	model	d-coeff.	AIC
ERO	(3,2)	0.011 (0.831)	1.144	169.189***	0.051 (0.310)	(2,3)	1.286 (0.000)***	0.870
DRR	(2,3)	-0.015 (0.726)	2.217	7.440***	-0.006 (0.064)	(3,3)	0.856 (0.000)***	2.123
CNY	(3,3)	-0.331 (0.000)***	-0.227	65.714***	-0.168 (0.180)	(1,1)	0.836 (0.000)***	-0.854
ICI	(0,2)	-0.130 (0.033)**	-0.238	13.320***	-0.069 (0.280)	(1,2)	0.565 (0.040)**	-0.374
URR	(2,2)	-0.043 (0.188)	2.770	10.471***	0.030 (0.810)	(2,3)	0.697 (0.010)***	2.670

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 3: Summary Statistics of Unit Root, LM, and ARMA-LM tests for stock index and ETN returns

ETNs	ADF	ARMA	AIC	LM-test	ARMA Res.	AIC	LM-test	ARCH-LM	GARCH Res.	AIC	ARCH-LM
ERO	-24.327***	(3,2)	1.124	2.919	(3,3)	1.114	0.970	174.758***	(2,2)	0.831	2.811
DRR	-27.928***	(2,3)	2.217	0.400	(0,1)	2.203	0.450	15.248***	(3,3)	1.849	1.849
CNY	-23.774***	(3,3)	-0.241	0.939	(3,2)	-0.264	0.425	65.563***	(2,3)	-0.826	0.114
ICI	-24.327***	(0,2)	-0.056	1.433	(2,3)	-0.065	0.610	121.542***	(1,1)	-0.375	7.395
URR	-20.090***	(2,2)	2.770	-0.043	(2,3)	2.755	0.527	28.555***	(3,3)	2.667	0.154

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

all the currency ETN returns through the Breush-Godfrey LM test. The Lagrange Multiplier Test (ARCH-LM) was used in testing for the ARCH effect (Engle, 1982). The relevant statistics of the ARMA returns and ARMA residuals models with the null hypothesis of no ARCH effect for all samples was rejected and fit for further testing for the GARCH residuals test. And for the last column, the results showed that there is no longer an ARCH effect for all of the samples.

4.2. Chaos methodology results: BDS test, R/S analysis and Correlation dimension analysis

This study conducted a series of test to detect chaos in the time-series data. The BDS is first of the three tests to detect chaos and rules out the possibility that the data behaves *iid*, followed by the R/S analysis and correlation dimension analysis to determine chaotic properties.

4.2.1. Brock, Dechert, and Scheinkman test results

The research used four values of ε/σ from 0.5 to 2.0 to cover both short and long dimensions which improve the power of the BDS test. Table 4 illustrates that the BDS statistics are significant at the 1% level for most values of ε/σ for the ETN returns and ARMA residuals. Thus, this paper can conclude that data sets are not *iid*, and conventional linear methodologies are not appropriate for their analysis, because the data is not a pure random series. In earlier studies, Eldridge et al. (1993) and Opong et al. (1999) finds similar findings of non-stochastic process in the S&P 500 cash index and returns of FTSE index, respectively. However, we cannot conclude the stochastic properties for all the GARCH residuals, except for CNY and URR ETNs. The presence of significant results from embedding dimensions 2-5 and values of ε/σ from 0.5-2.0 for CNY, and from embedding dimensions 3-6 and value of 0.5 ε/σ for URR mean that at least on a shorter dimension, a possibility of a chaotic series and not a random process may be present. Since BDS test is just the beginning in testing for chaos, this paper further tests its validity and utilizes rescaled range (R/S) and correlation dimension analyses to supplement this initial test.

4.2.2. Rescaled Range analysis: Hurst exponent results

Table 5 shows that all Hurst exponents of the currency ETN returns, ARMA and GARCH residuals are way below 0.5, however, after scrambling the data series, all Hurst exponents are

Table 4: BDS test for Currency ETNs

ERO	**ETN returns**				**ARMA residuals**				**GARCH residuals**			
ε / σ	0.5	1.0	1.5	2.0	0.5	1.0	1.5	2.0	0.5	1.0	1.5	2.0
2	0.005*** (0.007)	0.009*** (0.001)	0.000 (n/a)	0.006*** (0.001)	0.004*** (0.001)	0.010*** (0.000)	0.010*** (0.000)	0.008*** (0.000)	-0.001 (0.133)	-0.003 (0.165)	-0.002 (0.276)	-0.001 (0.589)
3	0.005*** (0.000)	0.016*** (0.000)	0.000 (n/a)	0.015*** (0.000)	0.004*** (0.000)	0.017*** (0.000)	0.023*** (0.000)	0.019*** (0.000)	-0.001 (0.134)	-0.002 (0.376)	-0.002 (0.514)	-0.001 (0.842)
4	0.004*** (0.000)	0.021*** (0.000)	0.000 (n/a)	0.026*** (0.000)	0.003*** (0.000)	0.021*** (0.000)	0.033*** (0.000)	0.031*** (0.000)	-0.000 (0.272)	-0.001 (0.457)	-0.003 (0.556)	-0.001 (0.775)
5	0.003*** (0.000)	0.025*** (0.000)	0.000 (n/a)	0.041*** (0.000)	0.002*** (0.000)	0.023*** (0.000)	0.045*** (0.000)	0.046*** (0.000)	-0.000 (0.812)	-0.001 (0.645)	-0.002 (0.692)	-0.001 (0.771)
6	0.001*** (0.000)	0.025*** (0.000)	0.000 (n/a)	0.055*** (0.000)	0.001*** (0.000)	0.023*** (0.000)	0.054*** (0.000)	0.060*** (0.000)	0.000 (0.503)	-0.000 (0.905)	-0.001 (0.825)	-0.001 (0.825)

DRR	**ETN returns**				**ARMA residuals**				**GARCH residuals**			
ε / σ	0.5	1.0	1.5	2.0	0.5	1.0	1.5	2.0	0.5	1.0	1.5	2.0
2	0.002*** (0.010)	0.006*** (0.005)	0.007*** (0.004)	0.005*** (0.002)	0.002** (0.016)	0.006*** (0.005)	0.006*** (0.008)	0.004*** (0.006)	-0.000 (0.540)	0.000 (0.829)	-0.000 (0.955)	0.000 (0.750)
3	0.002*** (0.000)	0.010*** (0.000)	0.015*** (0.000)	0.014*** (0.000)	0.001*** (0.004)	0.009*** (0.000)	0.013*** (0.000)	0.012*** (0.000)	-0.000 (0.606)	-0.001 (0.702)	-0.001 (0.639)	-0.000 (0.972)
4	0.001*** (0.000)	0.010*** (0.000)	0.021*** (0.000)	0.024*** (0.000)	0.001*** (0.000)	0.009*** (0.000)	0.019*** (0.000)	0.022*** (0.000)	0.000 (0.974)	-0.001 (0.426)	-0.003 (0.424)	-0.001 (0.724)
5	0.001*** (0.000)	0.009*** (0.000)	0.026*** (0.000)	0.033*** (0.000)	0.000*** (0.000)	0.007*** (0.000)	0.023*** (0.000)	0.030*** (0.000)	0.000 (0.641)	-0.001 (0.201)	-0.004 (0.304)	-0.003 (0.545)
6	0.000*** (0.000)	0.008*** (0.000)	0.028*** (0.000)	0.041*** (0.000)	0.000*** (0.000)	0.006*** (0.000)	0.025*** (0.000)	0.037*** (0.000)	0.000 (0.026)	-0.001 (0.326)	-0.003 (0.433)	-0.001 (0.618)

CNY	**ETN returns**				**ARMA residuals**				**GARCH residuals**			
ε / σ	0.5	1.0	1.5	2.0	0.5	1.0	1.5	2.0	0.5	1.0	1.5	2.0
2	0.037*** (0.000)	0.042*** (0.000)	0.031*** (0.000)	0.021*** (0.000)	0.030*** (0.000)	0.039*** (0.000)	0.029*** (0.000)	0.018*** (0.000)	-0.005*** (0.002)	-0.010*** (0.001)	-0.006*** (0.008)	-0.002* (0.097)
3	0.049*** (0.000)	0.077*** (0.000)	0.063*** (0.000)	0.044*** (0.000)	0.033*** (0.000)	0.068*** (0.000)	0.060*** (0.000)	0.045*** (0.000)	-0.004*** (0.004)	-0.012*** (0.006)	-0.012*** (0.007)	-0.008*** (0.008)
4	0.049*** (0.000)	0.106*** (0.000)	0.095*** (0.000)	0.069*** (0.000)	0.030*** (0.000)	0.092*** (0.000)	0.091*** (0.000)	0.071*** (0.000)	-0.002** (0.030)	-0.009** (0.046)	-0.013 (0.035)	-0.010** (0.021)
5	0.043*** (0.000)	0.126*** (0.000)	0.127*** (0.000)	0.093*** (0.000)	0.024*** (0.000)	0.107*** (0.000)	0.118*** (0.000)	0.097*** (0.000)	-0.001* (0.077)	-0.006 (0.144)	-0.011 (0.113)	-0.011* (0.061)
6	0.035*** (0.000)	0.141*** (0.000)	0.151*** (0.000)	0.115*** (0.000)	0.018*** (0.000)	0.118*** (0.000)	0.144*** (0.000)	0.122*** (0.000)	-0.001 (0.399)	-0.003 (0.438)	-0.007 (0.368)	-0.010 (0.188)

(continued)

ICI ε/σ	ETN returns 0.5	ETN returns 1.0	ETN returns 1.5	ETN returns 2.0	ARMA residuals 0.5	ARMA residuals 1.0	ARMA residuals 1.5	ARMA residuals 2.0	GARCH residuals 0.5	GARCH residuals 1.0	GARCH residuals 1.5	GARCH residuals 2.0
2	0.008*** (0.000)	0.019*** (0.000)	0.019*** (0.000)	0.014*** (0.000)	0.007*** (0.000)	0.017*** (0.000)	0.017*** (0.000)	0.012*** (0.000)	-0.001 (0.387)	-0.001 (0.786)	-0.000 (0.911)	0.000 (0.774)
3	0.009*** (0.000)	0.036*** (0.000)	0.041*** (0.000)	0.030*** (0.000)	0.008*** (0.000)	0.033*** (0.000)	0.040*** (0.000)	0.030*** (0.000)	-0.000 (0.612)	0.000 (0.930)	0.001 (0.823)	0.002 (0.544)
4	0.006*** (0.000)	0.042*** (0.000)	0.060*** (0.000)	0.046*** (0.000)	0.005*** (0.000)	0.041*** (0.000)	0.060*** (0.000)	0.048*** (0.000)	-0.000 (0.903)	0.001 (0.710)	0.001 (0.701)	0.003 (0.546)
5	0.004*** (0.000)	0.042*** (0.000)	0.075*** (0.000)	0.064*** (0.000)	0.003*** (0.000)	0.041*** (0.000)	0.076*** (0.000)	0.067*** (0.000)	-0.000*** (0.006)	0.001 (0.687)	0.002 (0.705)	0.004 (0.512)
6	0.002*** (0.000)	0.037*** (0.000)	0.083*** (0.000)	0.078*** (0.000)	0.002*** (0.000)	0.037*** (0.000)	0.084*** (0.000)	0.082*** (0.000)	-0.000*** (0.006)	-0.000 (0.997)	0.000 (0.986)	0.002 (0.707)

URR ε/σ	ETN returns 0.5	ETN returns 1.0	ETN returns 1.5	ETN returns 2.0	ARMA residuals 0.5	ARMA residuals 1.0	ARMA residuals 1.5	ARMA residuals 2.0	GARCH residuals 0.5	GARCH residuals 1.0	GARCH residuals 1.5	GARCH residuals 2.0
2	0.003** (0.028)	0.007** (0.018)	0.010*** (0.002)	-0.000*** (0.000)	0.002 (0.192)	0.005 (0.103)	0.008*** (0.010)	0.008*** (0.001)	-0.001 (0.300)	-0.003 (0.266)	-0.000 (0.863)	0.001 (0.717)
3	0.003*** (0.001)	0.016*** (0.000)	0.027*** (0.000)	-0.001*** (0.000)	0.002** (0.049)	0.011** (0.037)	0.022*** (0.000)	0.022*** (0.000)	-0.001* (0.100)	-0.003 (0.277)	-0.001 (0.871)	0.002 (0.606)
4	0.002*** (0.001)	0.015*** (0.000)	0.034*** (0.000)	-0.002*** (0.000)	0.001* (0.075)	0.011** (0.043)	0.028*** (0.000)	0.034*** (0.000)	-0.001** (0.019)	-0.004 (0.145)	-0.002 (0.695)	0.002 (0.680)
5	0.001*** (0.001)	0.013*** (0.000)	0.040*** (0.000)	-0.002*** (0.000)	0.001** (0.013)	0.010** (0.014)	0.033*** (0.000)	0.045*** (0.000)	-0.000** (0.027)	-0.003 (0.170)	-0.002 (0.760)	0.003 (0.607)
6	0.000*** (0.000)	0.010*** (0.000)	0.037*** (0.000)	-0.004*** (0.000)	0.000*** (0.002)	0.007*** (0.019)	0.031*** (0.000)	0.047*** (0.000)	-0.000** (0.030)	-0.003 (0.113)	-0.004 (0.484)	-0.001 (0.879)

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 5: Hurst exponents

Stock returns	**ERO**	**DRR**	**CNY**	**ICI**	**URR**
Original Series	-0.004440	0.000750	0.003648	-0.00144	0.000371
Scrambled Series	0.479791	0.518809	0.216550	0.396414	0.487579
ARMA residuals	**ERO**	**DRR**	**CNY**	**ICI**	**URR**
Original Series	0.000148	0.000253	0.000253	0.000289	0.000414
Scrambled Series	0.509586	0.508859	0.508859	0.476339	0.50562
GARCH residuals	**ERO**	**DRR**	**CNY**	**ICI**	**URR**
Original Series	0.000666	0.000504	-0.000340	-0.000340	0.000362
Scrambled Series	0.504446	0.521021	0.544587	0.544587	0.544807

Table 6: Correlation Dimension estimates

Correlation Dimensions	Embedding Dimensions									
	1	2	3	4	5	6	7	8	9	10
1. ERO ETN returns	1.174	1.996	2.791	3.391	3.887	4.504	4.453	4.978	4.998	4.911
ARMA residuals	1.025	2.013	2.95	3.567	3.975	4.461	4.643	5.201	4.723	5.195
GARCH residuals	0.994	1.957	2.554	3.17	3.787	3.825	4.292	4.266	4.647	4.989
2. DRR ETN returns	1.164	2.079	2.896	3.541	3.972	4.355	4.76	4.862	5.017	5.013
ARMA residuals	1.005	2.004	2.925	3.541	3.831	4.39	4.312	4.85	5.102	5.59
GARCH residuals	1.046	2.054	2.911	3.691	4.165	4.879	5.102	5.277	5.775	5.627
3. CNY ETN returns	0	2.255	3.16	3.87	4.300	4.683	4.99	5.191	5.749	5.653
ARMA residuals	1.056	2.012	2.789	3.368	3.683	3.95	3.797	4.153	4.607	4.066
GARCH residuals	1.021	1.926	2.624	3.061	3.606	3.81	4.146	4.546	4.099	4.438
4. ICI ETN returns	1.604	2.019	2.932	3.623	4.169	4.695	4.85	5.448	5.426	5.291
ARMA residuals	1.014	2.022	2.765	3.394	4.182	4.138	4.867	4.91	4.869	5.209
GARCH residuals	1.021	1.926	2.624	3.061	3.606	3.81	4.146	4.546	4.099	4.438
5. URR ETN returns	1.002	2.113	3.127	3.92	4.474	5.079	5.486	5.848	5.874	n.v.
ARMA residuals	1.079	2.185	3.116	3.743	4.443	4.482	5.206	4.456	4.818	5.244
GARCH residuals	1.044	2.086	2.986	3.682	4.193	4.828	4.709	5.275	5.011	5.028

Note: n.v. – no value

significantly asymptotic to 0.5. These findings are consistent with Peters (1994)[1] and Opong et al. (1999), and in the expectations of this paper. This research also concludes that currency ETNs have persistent and trend-reinforcing series, in which having an upward (downward) trend in the last period, will continue to be positive (negative) in the following period.

4.2.3. Correlation Dimension Analysis results

The last test done to finally conclude for the chaotic properties of currency ETN returns is shown in Table 6, wherein the correlation dimension estimates were utilized. This paper observed that as the embedding dimensions gradually increased from 1 to 10, the correlation dimension generally increases. This behavior tells that the underlying data of ETN returns, ARMA and GARCH residuals is consistent with chaos as defined by Wei and Leuthold (1998). Thus, this paper concludes the currency ETN returns are consistent with chaos and these findings also conforms to the study of Kyrtsou et al. (2004) of the French CAC40 index returns.

In sum, the ARFIMA-FIGARCH models generally concluded that the returns structure cannot be generated by any autoregressive (AR) model which is a type of a stochastic process, while the volatility structure was defined to have long-memory properties and non-stationary. Further tests showed that currency ETN returns, ARMA residuals and GARCH residuals are consistent with deterministic chaos, which explains the initial results of ARFIMA-FIGARCH processes of deterministic properties. The economic implication of these findings is that practitioners should be cautious in trying to predict return and volatility movements of currency ETNs using AR processes. They would generally find misleading forecast that maybe detrimental to possible earnings of profits and worse can create losses, because the inherent structure is defined by chaotic properties.

5 Conclusions

This paper utilized ARFIMA-FIGARCH models to indentify long-memory properties of currency ETNs. The study found that the returns of CNY and ICI ETNs exhibited a non-invertible stationary process. For the return volatility outcomes of the FIGARCH model, ERO ETN sample showed non-stationarity and is also difficult to model. However, the volatility structure of the remaining DRR, CNY, ICI and URR returns exhibited long-memory processes in their volatility structures. Since the study samples showed non-stationarity and non-invertibility properties, but with enough evidence to prove its long-memory

[1] Peters (1994) explained that if a time-series is determined by a chaotic process, the Hurst exponent, which developed by Hurst (1951) would be much closer to 0.5 after scrambling the data than the one before scrambling.

properties, these make us conclude that the efficient market hypothesis of Fama (1970) did not apply for the volatility of currency ETNs. The tendency of currency ETN returns to eventually move back towards the average rate in the long-run is a possibility.

To further understand their behavior, BDS, R/S Analysis and Correlation Dimension tests were applied and concluded that the time-series showed evidences of chaos. The BDS test found that ETN returns and ARMA residuals are not *iid*, and that conventional linear methodsare not suited for their analysis. This test initially cannot ensure the *iid* properties of GARCH residuals, except for CNY and URR. However, when the R/S analysis was conducted, all Hurst exponents of the currency ETN returns, ARMA and GARCH residuals became significantly asymptotic to 0.5 after scrambling the data which means that a chaotic tendency is present. This study also concludes that the data have persistent and trend-reinforcing series. The correlation dimension analyses was also used to supplement the first two tests and observed that as the embedding dimensions gradually increased from 1 to 10, the correlation dimension generally increases, further confirming a deterministic chaos for the time-series.

Fund managers and traders attempting to forecast return and volatility of currency ETNs utilizing AR processes would fail to incur additional gains and in worse cases may suffer losses, because their behavior is inherently chaotic. Also, general stakeholders like the government and the investing public will have a good working knowledge of the nonlinear properties of ETNs in helping them make informed choices based on their risk preferences in selecting currency ETNs for investments. On the other end, the findings can also solidify or melt present knowledge of academicians from the pool of financial time-series literatures, and also lead their future studies to further explore huge unchartered territories of ETNs. Researchers will be able to gain some insights on the tendencies of this new investment and at the same time acquire some ideas on some possible models that can be applied to other financial instruments.

References

[1] Adrangi, B., Allender, M., Chatrath, A. and Raffiee, K., Nonlinearities and chaos: Evidence from exchange rates, Atlantic Economic Journal, 38(2), (2010), 247-248.

[2] Antoniou, A. and Vorlow, C., Price clustering and discreteness: Is there chaos behind noise?, Physica A, 348, (2005) , 389-403.

[3] Baillie, R., Long memory processes and fractional integration in econometrics, Journal of Econometrics, 7, (1996), 35-59.

[4] Baillie, R., Bollerslev, T. and Mikkelsen, H., Fractionally integrated generalized autoregressive conditional heteroskedasticity, Journal of Econometrics, 74, (1996), 3–30.

[5] Beine, M., Laurent, S. and Lecourt, C., Accounting for conditional leptokurtosis and closing days effects in FIGARCH models of daily exchange rates, Applied Financial Economics, 12(8), (2002), 589-600.
[6] Blank, S., Chaos in futures markets? A non-linear dynamical analysis. Journal of Futures Markets, 11, (1991), 711-728.
[7] Box, G. and Jenkins, G., Time series analysis, forecasting and control, Holden Day, San Francisco, (1976).
[8] Brock, W., Dechert, W. and Scheinkman, J. (1996) A test for independence based on correlation dimension, Econometric Reviews, 15(3), 197-235.
[9] Bubak, V., Kocenda, E. and Ikes, F., Volatility transmission in emerging European foreign exchange markets, Journal of Banking and Finance, 10, (2011), 1-13.
[10] Cai, F., Howorka, E. and Wongsman, J., Informational linkages across trading regions: Evidence from foreign exchange markets, Journal of International Money and Finance, 27, (2008), 1215-1243.
[11] Choi, K. and Hammoudeh, S., Long memory in oil and refined products markets, Energy Journal, 30(2), (2009), 97-116.
[12] Das, A. and Das, P., Chaotic analysis of the foreign exchange rates, Applied Mathematics and Computation, 185, (2007), 388-396.
[13] Eldridge, M., Bernhardt, C and Mulvey, I., Evidence of chaos in the S&P 500 cash index, Advances in Futures and Options Research, 6, (1993), 179-192.
[14] Enders, W. Applied econometric time series, Hoboken, NJ: John Wiley & Sons, (2004).
[15] Engle, R. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, Econometrica, 50, (1982), 987-1007.
[16] Fama, E., Efficient capital markets: A review of theory and empirical work, Journal of Finance, 2, (1970), 383-417.
[17] Granger, C. and Joyeux, R., An introduction to long memory time series models and fractional differencing, Journal of Time Series Analysis, 1, (1980), 15-39.
[18] Grassberger, P. and Procaccia, I., Measuring the strangeness of strange attractors, Physica D, 9, (1983), 189-208.
[19] Hafner, C., and Herwartz, H., Volatility impulse responses for MGARCH models: An exchange rate illustration, Journal of International Money and Finance, 25, (2006), 719-740.
[20] Henry, O. and Olekalns, N., Does the Australian dollar real exchange rate display mean reversion, Journal of International Money and Finance, 21, (2002), 651-666.
[21] Hsieh, D., Chaos and nonlinear dynamics: Application to financial markets, Journal of Finance, 46, (1991), 1839-1877.
[22] Hosking, J., Fractional differencing, Biometrika, 68, (1981), 165-176.
[23] Hurst, H., Long-term storage capacity of resevoirs, Transactions of the American Society of Civil Engineers, 116, (1951), 770-799.
[24] Jin, Y., Competitions hatch butterfly attractors in foreign exchange markets,

Physica A; 348, (2005), 380-388.

[25] Kang, S.H. and Yoon, S.M., Long memory properties in return and volatility: Evidence from the Korean stock market, Statistical Mechanics and Its Applications, 385(2), (2007), 591-600.

[26] Korkmaz, T., Cevik, E. and Ozatac, N., Testing for long memory in ISE using ARFIMA-FIGARCH model and structural break test, International Research Journal of Finance and Economics, 26, (2009), 188-191.

[27] Kyrtsou, C., Labys, W. and Terraza, M., Noisy chaotic dynamics in commodity markets, Empirical Economics, 29(3), (2004), 489-502.

[28] Kyrtsou, C. and Terraza, M., Stochastic chaos or ARCH effects in stock series?, International Review of Financial Analysis, 11, (2002), 407-431.

[29] Mandelbrot, B. and Wallis, R., Robustness of the rescaled range R/S in the measurement of noncyclic long-run statistical dependence, Water Resources Research, 5, (1969), 967-988.

[30] Mariani, M., Libbin, J., Martin, K. Ncheuguim, E., Beccar, M. Varela,V., Mani, K. Erickson, C. and Valles-Rosales, D. Levy models and long correlations applied to the study of exchange traded funds, International Journal of Computer Mathematics, 86(6), (2009), 1040-53.

[31] Moshiri, S. and Faezeh, F., Forecasting nonlinear crude oil futures prices, Energy Journal, 27, (2006), 81-95.

[32] Nouira, L., Ahamada, I., Jouini, J. and Nurbel, A., Long-memory and shifts in the unconditional variance in the exchange rate Euro/US Dollar returns, Applied Economics Letters, 11, (2004), 591-594.

[33] Opong, K., Mulholland, G., Fox, A. and Farahmand, K., The behaviour of some UK equity indices: An application of Hurst and BDS tests, Journal of Empirical Finance, 6, (1999), 267-282.

[34] Panas, E., Long memory and chaotic models of prices on the London Metal Exchange, Resource Policy, 27, (2001), 235-246.

[35] Panas, E. and Ninni, V. Are oil prices chaotic? A non-linear dynamic analysis, Energy Economics, 22, (2000), 549-568.

[36] Peters, E., Fractal market analysis: Applying chaos theory to investment and Economics, Wiley: New York, (1994).

[37] Rompotis, G., Predictable patterns in ETFs' return and tracking error, Studies in Economics and Finance, 28(1), (2011), 14-35.

[38] Serletis, A. and Gogas, P., The North American natural gas liquids markets are chaotic, Energy Journal, 1(20), (1999), 83-103.

[39] Smith, J. Small, K., Weighing the risks: Are exchange-traded notes right for your clients? Journal of Financial Planning, 23(10), (2010), 56-65.

[40] Tan, S. and Khan, M., Long memory features in return volatility of the Malaysian stock market, Economics Bulletin, 30(4), (2010), 3267-81.

[41] Wallis, J. and Matalas, N., Small sample properties of H&K estimators of the Hurst Coefficient, Water Resources Research, 6, (1970), 1583-1594.

[42] Washer, K. and Jorgensen, R., Exchange-traded notes and the Lehman bankruptcy, Academy of Accounting and Financial Studies Journal, 15(1),

(2011), 47-57.

[43] Wei, A. and Leuthold, R. Long agricultural prices: ARCH, long memory or chaos processes? OFOR Paper No. 98-03, (1998).

[44] Wright, C., Diavatopoulos, D. and Felton, J., Exchange-traded notes: An introduction, Journal of Investing, 19(2), (2010), 27-30.

[45] Yang, J., Cabrera, J. and Wang, T., Nonlinearity, data-snooping, and stock index ETF return predictability, European Journal of Operational Research, 200(2), (2010) 498-507.

[46] Yudin, A., From chaos to trends in forex, Futures: News, Analysis and Strategies for Futures, Options and Derivatives Traders, 37(4), (2008), 38-40.

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