Empirical Study on the Existence of Long-term Memory In the Philippine Foreign Exchange Market

Ahmadreza Fouladi
Azad University, Tehran, Iran
ahmadreza.fouladi@gmail.com

This article examines twenty-two foreign exchange currencies **vis-a-vis** the Philippine peso for evidence of long-term dependence. This study uses three different methods: the classical rescaled range and the modified rescaled range of Andrew Lo (1991), and the rescaled variance statistic of Giraitis et al. (2003). This study also makes a comparative analysis using these three methods between the peso and twenty-two other foreign currencies. These empirical tests are conducted with daily data obtained during the period of January to December 2010. Using the modified rescaled range and the rescaled variance methods, we show that there is no significant long-range dependence in all examined currencies; however when using the classical rescaled range, we detect significant long-range dependence in many cases. The ARFIMA modeling also performed for those, showed long-term memory. The software-based tools compatible with MATLAB and Excel software are also developed to ease the arduous process of testing and finding the existence of long-range dependence in financial market time series datasets, based on modified rescaled range and rescaled variance statistics.

Keywords: long-term memory, foreign exchange markets, Philippine, rescaled range analysis, Hurst exponent, ARFIMA modeling

INTRODUCTION

Given the lack of agreement on the existence of long-term memory process in currency exchange rate returns, it is important to study this phenomenon further by using more powerful methodologies and techniques. The long-term behavior of discrete time dynamical systems in economics and finance has gained much attention in recent years. Understanding exchange rates dynamics has important economic implications, since flows and prices of tradable goods and international asset portfolios are closely related to these dynamics; and based on these structure characteristics, the market can be categorized under one of these controversial market hypotheses: Peters (1994) claimed that the Fractal Market Hypothesis (FMH) explains long-term memory in the financial branch, which cannot be explained by the Efficient Market Hypothesis. This Fractal Market Hypothesis is based on Chaos Theory and it could present an alternative to the Efficient Market Hypothesis. Various tools for detecting possible long memory in time series were proposed in econometric and statistical literatures.

In this paper, an empirical investigation of the return behavior of twenty-two foreign currencies versus the peso is conducted in order to detect possible dependency. The first objective of this paper, therefore, is to examine the nature of dependency in foreign exchange rates, as well as investigate the characteristics of the Philippine currency market. In order to achieve this goal this paper covers and employs three methods, including: the classical rescaled range, the modified rescaled range and the rescaled variance statistic, to detect the existence of long-range dependency; it also makes a comparative analysis using these three methods between the peso and twenty-two other foreign currencies. The second objective of this study is to identify the most appropriate ARFIMA model that could be employed to aid in forecasting the currencies that exhibit long memory characteristics. ARFIMA was found by Hosking (1981) to be more appropriate in capturing long range dependence for modeling persistent, that is, long memory, time series processes.

The third objective of the study is to develop a software-based financial tool for the modified rescaled range statistic based on Andrew Lo's (1991) methodology; and also for rescaled variance statistics based on Giritais et al.'s (2003) methodology, to ease the process of testing and finding the existence of long-range dependence in financial market time series dataset. This would be done due to the lack of a specific software-based tool that uses these methods. These tools would have the ability and flexibility to execute the test under different bandwidth parameters, series length and various confidence interval and related critical values, to accept or reject the null hypothesis of no long-range dependency. The results of the software-based tool would then be compared with the results derived from implementing a step-by-step procedure using direct formulas to verify the validity and accuracy of the tool's results.

Long run persistence or long memory in asset returns has important implications for the ability to predict future returns; and, therefore, for investment decisions that pertain to the effective allocation of resources. A study of long memory, therefore, should be of interest to investors and other agents who closely examine financial markets with the aim of generating trading profits. Knowing the results of long-term memory in a market could be beneficial for individuals and speculators who are involved in the foreign exchange market, by giving them a perspective on the nature or characteristics of this market in terms of the dependency of the respective currency, so that they can choose proper models and strategies to suit their purpose. Academicians and future researchers can also use this study for further research by identifying research gaps and areas that needed to be focused on, more specifically in more recent data collection. This paper contributes to the existing literature by focusing on a large group of exchange rates that include a variety of countries from different regions of the world.

If one can find evidence of long-range dependency, then this could be incorporated and considered in pricing models and also in portfolio and risk management, because most of financial theory relies on the hypothesis that returns do not present long term memory. There is no consensus among researchers on the existence of short or long memory in financial markets; and it is not yet clear whether this controversy is due to the nature of the different data sets employed in terms of currencies, markets, sample size, noise level, etc., or to the testing framework that has been adopted. With respect to the latter, it is interesting to note that studies using classical R/S analysis seem to support a long-term dependence hypothesis; while the opposite seems to be the case for the modified R/S and rescaled variance statistic. Taking into account that, so far, the results of similar researches have not yet established a general character of currency markets, this analysis is expected to be useful for comparative purposes as well, by using these three methods.

On the other hand, developing the software-based tools could accelerate the process of testing which include burdensome computations if one uses direct formulas; so these tools would ease the process for testing and finding the existence of long-range dependency in financial market time series dataset. Moreover, users can easily test their data for a specific market; and based on the outcome, they can choose financial models and/or strategies which are consistent with the results.

The focus of this paper is on the Philippine currency market or exchange rate market, the peso against selected currencies. The observation for analysis covers the peso exchange rate versus twenty- two other currencies , namely: Australian dollar (AUD), Canada dollar (CAD), US dollar (USD), British pound sterling (GBP), Hong Kong dollar (HKD), Japanese yen (JPY), Malaysian ringgit (MYR), New Zealand dollar (NZD), Singapore dollar (SGD), Thailand baht (TBH), Swiss franc (CHF), Indonesian dupiah (IDR), Brunei Dollar (BND), Euro (EUR), Saudi riyal (SAR), Bahraini dinars (BHD), UAE dirham (AED), Brazilian real (BRL), Danish croner (DKK), Indian rupees (INR), Mexican pesos (MXN) and *Norwegian kroner (NOK)*. These currencies were chosen due to data restriction. For other currencies against the peso, there was limited or no historical data for the desired period of study. The analysis covers the last two decades, the 20-year period of 1991 to 2010, except for Euro and UAE which only covers the period of 1999 to 2010, due to data limitation. Data coverage in this period is seamless and has no interruption.

In this paper, long-term memory is estimated using the following approaches:

1-**Classical Rescaled range (R/S) -** a prevalent framework for detecting long-range dynamics in time series, originated by Hurst (1951) and further developed by Mandelbrot (1969);

2-**Modified Rescaled Range -** Andrew Lo (1991) proposed a modified version of the R/S statistic by correcting two shortcomings of it;

3-**Rescaled Variance -** another non-parametric test, known as the rescaled variance test, or the V/S statistic, proposed by Giraitis et al. (2003).

All three techniques (classical R/S analysis, modified R/S analysis and V-statistic) shall examine the null hypothesis (H_0) of no long-range dependence in the time series of the Philippine currency against a particular foreign currency. By using the classical rescaled range model, Hurst exponent (H) is estimated in order to derive the inference of long memory or short memory. Classical R/S analysis has been applied to various financial markets, and in almost all cases long-term memory has been reported. It is a measure of the predictability of a time series. León and Reveiz (2010) explained two common problems with estimating H by classical R/S analysis. First, there is a positive bias in the estimation or overestimation of H resulting from finite time-series and minimum size of periods. Second, derived H for normal and non-normal distributed random variables follows a normal distribution. Estimating the Hurst exponent as a measure for long-term dependency requires the design of significance tests for evaluating the null hypothesis of independence. Teverovsky et al. (1999) claimed that classical R/S analysis is clearly not reliable for small samples, but it can be highly effective and useful as a graphical or `eye balling' method for reasonably large samples. With regard to less attractive features of the classical R/S-analysis which are: its sensitivity to the presence of explicit short-range dependence structures; its bias; and a lack of a distribution theory for the underlying statistic,; Andrew Lo (1991) proposed a modified version of the R/S statistic and applied it to different markets and datasets; his studies have reported a weak long-term dependence or its absence. Lo's (1991) modified R/S statistic corrects two shortcomings of the classical R/S statistic by allowing for short-term dependence and heteroskedasticity. He derives the limiting distribution of his modified R/S statistic and illustrates through Monte-Carlo simulations that it has reasonable power against certain long-range dependence alternatives. By providing the sampling theory, the modified R/S statistic can be tested statistically with its limiting distribution.

Teverovsky et al. (1999) and Willinger et al. (1999) have found that the modified R/S statistic is biased in favor of accepting the null hypothesis of no long-range dependence as the bandwidth parameter increases. These authors cautioned against using Lo's modified R/S test in isolation. For this reason, this study used another non-parametric test for comparison, known as the rescaled variance test, or the V/S statistic, proposed by Giraitis et al. (2003). The V/S statistic differs from other tests in this range by correction for a mean; it is shown to have a simpler asymptotic distribution and to achieve a better balance of size and power than the other two tests. These characteristics make the V/S test more suitable for time series that exhibits high volatility, like the foreign exchange market. In the Monte Carlo studies performed by Giraitis et al. (2003), the V/S test is shown to be less sensitive to the choice of the bandwidth parameter; and it achieves a better balance of size and power than Lo's modified R/S statistic. These tests have certain advantages and disadvantages and suffer from problems that can seriously affect their results.

When a time series exhibits long-term memory, it contradicts the weak form of efficient market hypothesis and would allow investors to anticipate price movements and earn positive average returns; and according to Peters (1994) it would be classified under fractal market hypothesis. Financial researchers are continuously trying to improve the mathematical models that reliably identify the stochastic pricing processes of the financial markets. Traditional models describing short-term memory, such as AR (p), MA (q), ARMA (p, q), and ARIMA (q, d, q), cannot precisely describe long-term memory. A set of models have been established to overcome this difficulty, and the most common is the autoregressive fractionally integrated moving average (ARFIMA or ARFIMA(p, d, q)) model. The ARFIMA model was established by Granger and Joyeux (1980); it is an extended version of Box-Jenkins (1976) or ARIMA iterative modeling. They showed that it is possible to provide this model with long-range dependence properties by allowing the differencing parameter (d) to take on fractional values (real values) in ARIMA models. Hosking (1996) derived the bias, variance, and asymptotic distribution of the sample mean, and autocorrelations of long-term memory time series. Furthermore, he employed these characteristics in ARFIMA model. Bhardwaj and Swanson (2006) analyzed the predictive ability of ARFIMA models, using three financial and macroeconomic data sets. They employed a variety of long-memory testing and estimation procedures and evaluated the forecasting ability of ARFIMA models against standard short-memory models. Their results show that ARFIMA models are able to approximate the true data-generating process, and sometimes to perform significantly better in out-of-sample forecasting than simple short-memory models do. They also observed that ARFIMA models are, often superior in terms of forecasting ability even though they are less parsimonious than ARMA models, in terms of the additional parameter d and the ad-hoc application of the truncation lag.

METHODOLOGY

Classical Rescaled Range

Hurst (1951) put forward a statistic as Hurst Exponent to test long memory. He used the R/S method to analyze the fractal time series. The main idea behind the R/S analysis is that one looks at the scaling behavior of the rescaled cumulative deviations from the mean, or the distance the system travels as a function of time. General form of the R/S method is (Hurst, 1951): $(R/S)_n$

= Cn^H , where R is rescaled extreme difference, S is standard deviation, n is increased time length, C is constant, H is Hurst Exponent. By taking the logarithm of both sides of the above equation, the equation below is derived:

$$\log (R/S)_n = \log (c) + H * \log(n) \quad (1)$$

The Hurst exponent can be estimated by performing an ordinary least squares regression using (1) formula. In this regression, log(n) is the independent variable (X-axis) and log $(R/S)_n$ is the dependent variable (Y-axis). The intercept is the estimate for log (c) (the constant). The slope of the equation is the estimate of the Hurst exponent H. The general formula for $(R/S)_n$ is as below according to Peters (1994):

$$(R/S)_n \equiv \frac{[\underset{1\le k\le n}{Max}\sum_{i=1}^{k}(X_i-\overline{X}_n)-\underset{1\le k\le n}{Min}\sum_{i=1}^{k}(X_i-\overline{X}_n)]}{(\frac{1}{n}\sum_{i=1}^{n}(X_i-\overline{X}_n)^2)^{1/2}} \quad (2)$$

By choosing different values for n which represents the length of sub-series of main time series, one can compute respective $(R/S)_n$ for various n; consequently, Hurst exponent can be estimated by using a linear regression analysis related to (1) formula. The steps and procedures to compute the values of $(R/S)_n$ for respective values of n, according to Peters's, (1994) methodology are: Beginning with a time series of closing price $\{P_1, P_2, P_3 \dots P_M\}$ with length M (M observation). Convert it into a time series of logarithmic return by using (3) formula. The length of the return time-series which is derived by this formula is N that is equal to "M-1"

$$X_i = \ln (P_{(i+1)}/P_i), \quad i = 1, 2, 3, \dots, N \quad (3)$$

So the time series of return is $\{X_1, X_2, X_3, \dots, X_N\}$ with length N (N observation). In the next step, this time series of return is divided into A contiguous sub-series of length n, such that A*n = N. Label each sub-series by I_a, where a = 1, 2, 3, ..., A.; so in each sub-series (I_a) there are n observation: $\{X_{1,Ia}, X_{2,Ia}, \dots, X_{k,Ia}\}$ for k=1,2,3….,n; for each I_a of length n, the average value is defined as:

$$\overline{X}_{Ia} = (1/n) * \sum_{k=1}^{n} X_{k,Ia} \quad (4)$$

where $\overline{X}_{Ia}$ is equal to average value of every sub-series Ia of length n. in the next step deviation of each observation in sub-series from its respective average value will be computed and then the cumulative sum series of these deviation values will be constructed, which is denoted by $Y_{k,Ia}$ which contains: $\{Y_{1,Ia}, Y_{2,Ia}, \dots, Y_{k,Ia}\}$ for k=1,2,3….,n. The formula below is used for this purpose:

$$\overline{Y}_{k,Ia} = \sum_{k=1}^{n}\left(Y_{k,Ia} - \overline{X}_{Ia}\right) \quad (5)$$

The range is defined as the maximum minus the minimum value of $Y_{k,Ia}$ within each sub-series Ia:

$$RIa = \max (Y_{k,Ia}) - \min (Y_{k,Ia}) \quad (6)$$
where $1 \le k \le n$.

The sample standard deviation can be calculated for each sub-series Ia by using the following formula (7):

$$S_{Ia} = \sqrt{\frac{1}{n} * \sum_{k=1}^{n}\left(X_{k,Ia} - \overline{X}_{Ia}\right)^2} \quad (7)$$

Now each range, R_{Ia}, is normalized by dividing by the S_{Ia} corresponding to it. Therefore, the rescaled range for each Ia sub-series is equal to R_{Ia} / S_{Ia}. So for A contiguous sub-series of length n the average $(R/S)_n$ value can be obtained using the following formula (8):

$$(R/S)_n = (1/A) * \sum_{a=1}^{A}\left(R_{Ia} - S_{Ia}\right) \quad (8)$$

These steps repeat for other values of n and related contiguous sub-series until n = N/2. Then by using (1) equation, ordinary least squares regression on log(n) as the independent variable and log $(R/S)_n$ as the dependent variable, can be performed. The intercept is the estimate for log (c), the constant. The slope of the equation is the estimate of the Hurst exponent H. If H=0.5, which means they are not correlated and indicates no long memory; if $0 \leq H < 0.5$, this means they are negatively correlated; if $0.5 < H < 1$, this means they are positively correlated and the time series has long-term memory. León and Reveiz (2010) explained that one of the main difficulties of the R/S methodology is the selection of an ad-hoc optimal size of periods (n) to calculate $(R/S)_n$. there is no consensus on an optimal minimum size of periods (n_{min}). The same issue arises with the choice of optimal maximum period size (n_{max}). León and Reveiz acknowledge that financial series is not long enough to discard reduced windows, and suggest using at least 32 observations ($n_{min} \geq 2^5$). Cannon et al. (1997) estimated optimal minimum size of periods to be $n_{min} \geq 2^8$ (≥ 256 observations) to achieve standard deviations below 0.05.

Estimating the Hurst exponent ($\widehat{H}$) requires the design of significance tests for evaluating the null hypothesis of independence. There is a positive bias in the estimation –overestimation- of H resulting from a finite time-series. Several assessment methods for estimating such bias have been documented, but this work focuses on the single most well-known. First proposed by Anis and Lloyd (1976), and subsequently revised by Peters (1994), this method yields the expected Hurst exponent corresponding to an independent random variable, which will be noted as ($\dot{H}$). Ellis (2007) claimed that in the absence of a bootstrap or Monte Carlo mean for the Hurst exponent, the Anis and Lloyd (1976) and Peters (1994) expected rescaled range may be used to proxy the variable of expected Hurst exponent, which exists in the significant test of estimated Hurst exponent. So, value of ($\dot{H}$) can be derived by the following calculation of the expected value of (R/S)n:

$$E(R/S)_n = \left(\frac{n-0.5}{n}\right) * \sqrt{\frac{2}{n\pi}} * \sum_{r-1}^{n-1}\left(\frac{n-r}{n}\right) \quad (9)$$

Any divergence of ($\widehat{H}$) from ($\dot{H}$) would signal the presence of long-term memory in time-series. It is critical to develop appropriate statistical tests to distinguish between significant and non-significant deviations from the expected value. The above formula for expected rescaled range E(R/S) may be used to proxy the variable E(H) or $\widehat{\mu}\,(\dot{H})$ in the statistical test equation below. Based on Ellis's (2007) study this expected value is close to the result derived from Monte Carlo simulation. So, a conventional t-statistic test may be implemented. Let $\widehat{H}$ be the R/S's estimated value of the Hurst exponent, $\widehat{\mu}\,(\dot{H})$ and $\widehat{\sigma}\,(\dot{H})$ the expected value and standard deviation of the expected Hurst exponent corresponding to an independent random variable ($\dot{H}$); the significance test would be as follows:

$$t = \frac{\widehat{H} - \widehat{\mu}\,(\dot{H})}{\widehat{\sigma}\,(\dot{H})} \quad (10)$$

The significance measure uses the central limit theorem (CLT) to replace the standard deviation of the sampling distribution of the mean $\sigma/\sqrt{N}$ in the denominator of the above equation with its estimate $\widehat{\sigma}(\dot{H}) \approx 1/\sqrt{N}$ (Peters,1994). Ellis states that the result of above t-equation is the equivalent z-statistic for the required level of confidence. That is a significance measure in excess of related t-value derived from t-table; it would indicate, with specific confidence interval, that the observed Hurst exponent is/is not statistically different from its expected value. So, if estimated Hurst value would be significantly greater than its expected value ($\widehat{H} - \widehat{\mu}\,(\dot{H}) > 0$), the null hypothesis of no long-term dependence can be rejected.

Modified Rescaled Range

The classical R/S test has been proven to be too weak to indicate a true long-memory process; it is very sensitive to the presence of short memory, heteroskedasticity and multiple scale behavior. In the R/S method, the range relies on maximum and minimum; it makes the method error-prone because any outlier present in the data would have a strong influence on the range (Mukherjee and Sarkar, 2011). Lo (1991) therefore considered a modified R/S statistic in which short-run dependence is incorporated into its denominator, adding some weights and covariance estimators to the standard deviation. This adjustability for possible short memory effects has been made by applying the Newey-West Heteroscedasticity and autocorrelation consistent estimator in place of the sample standard deviation. For a given return series Xi; i=1, 2, . . . , N; Andrew Lo (1991) defines the modified R/S statistic as:

$$V(q)_N \equiv \frac{[\underset{1\le k\le N}{Max}\sum_{j=1}^{k}(X_j-\overline{X}_N)-\underset{1\le k\le N}{Min}\sum_{j=1}^{k}(X_j-\overline{X}_N)]}{\sqrt{N}(\frac{1}{N}\sum_{j=1}^{N}(X_j-\overline{X}_N)^2+\frac{2}{N}\sum_{j=1}^{q}(1-\frac{j}{q+1})[\sum_{i=j+1}^{N}(X_i-\overline{X}_N)(X_{i-j}-\overline{X}_N)])^{1/2}} \quad (11)$$

where $\overline{X}_N$ is the mean return for all n observations. Andrews (1991) provides a data-dependent rule for choosing the lag length q in the numerator of formula (11). The optimal lag (q) is given by Andrews in formula (12) below:

$$q^* = [K_n];\ K_n = (\frac{3N}{2})^{1/3}(\frac{2\rho}{1-\rho^2})^{2/3} \quad (12)$$

where [Kn] denotes the greatest integer less than or equal to q^*, and ρ is the estimated first-order autocorrelation coefficient of the data (Batten et al., 2000). The classical R/S statistic corresponds to q =0. Lo has shown that by allowing q to increase slowly with the sample size, asymptotic distribution of $V_N \equiv V_N$ (q) is parameter free and robust to many forms of weak dependence in the data. If "q" is too small, this statistic does not account for the autocorrelation of the process; while if q is too large, it accounts for any form of autocorrelation and the power of this test tends to its size. For these reasons, we will use different values for q below and above the optimal value. We considered the following values for q = 0,5,10,15,20,25,30,35,40 in this paper.

V_N (q) is usually constructed for a specific investment horizon and compared to critical values constructed by Lo. He derives the limiting distribution of the modified statistic which, as he notes, converges to the range of the standard Brownian bridge. The critical values of significant levels are computed and tabulated for the purpose of the hypothesis test under the null hypothesis of short-term dependence against long-term dependence alternatives. The critical values of the test derived by the asymptotic cumulative distribution function are given in Table 1.

Table 1

Asymptotic critical values of the modified R/S statistic

Probability level (P(V<X))	0.5%	2.5%	5%	10%	90%	95%	97.5%	99.5%
Critical value (X)	0.721	0.809	0.861	0.927	1.620	1.747	1.862	2.098

(The complete table can be found in Lo (1991) table)

Lo (1991) and Alptekin (2006) used a two-tailed test with the interval [0.809, 1.862] as the 95% (asymptotic) acceptance region for testing the null hypothesis of short-range dependence. If the estimated values are outside this range, null hypothesis of no long-range dependence could be rejected and the alternative of long-range dependence accepted.

Rescaled Variance (V/S)

The *V/S* statistic is the sample variance of the series of partial sums. The limiting distribution of this statistic is a Brownian bridge the distribution of which is linked to the Kolmogorov statistic. The asymptotic distribution of the V/S statistic has a simple form so that asymptotic critical values can be found using a table of the standard Kolmogorov statistic. The V/S is less sensitive than the Lo statistic to the choice of the order q. The idea behind the V/S analysis is quite similar to the modified R/S analysis. The only difference is that the range in the R/S analysis is replaced by the sample variance. This replacement makes better statistical power against long-range dependence even in square of returns, and thus in the volatility of financial time series (Giraitis et al., 2003). Giraitis et al. (2003) proposed a centering in the KPSS statistic and considered the following statistic (with notation of M), which they called V/S or rescaled variance statistic. The V/S in the title comes from variance over S, as the statistic $M(q)_N$ has the following form:

$$M(q)_N \equiv \frac{[Var(S_1^*, \cdots, S_N^*)]}{N(\frac{1}{N}\sum_{j=1}^{N}(X_j - \bar{X}_N)^2 + \frac{2}{N}\sum_{j=1}^{q}(1 - \frac{j}{q+1})[\sum_{i=j+1}^{N}(X_i - \bar{X}_N)(X_{i-j} - \bar{X}_N)])} \quad (13)$$

where $S_k^* = \sum_{j=1}^{k}\left(x_j - \bar{x}\right)$ is the partial sums of return series $\{x_t\}$. Here also we use Andrews's (1991) data-dependent procedure for determining the optimal bandwidth parameter q. Ahking (2010) derived the critical value for statistical tests, after a transformation of the standard Kolmogorov statistic described in Giraitis et al. (2003). The critical values at the 99%, 95%, 90% confidence level are 0.2685, 0.1869 and 0.1518, respectively. These critical values have also been confirmed in studies conducted by Caporale and Gil-Alana (2009), Assaf (2004 and 2008) and Alptekin (2006). Based on these critical values, if test result exceeds these values for specific significant level, one can reject the null hypothesis of no long-term dependence for an alternative hypothesis of long-term dependence.

Autoregressive Fractionally Integrated Moving Average (ARFIMA) for modeling

If the tests in previous parts show long memory, according to Hosking (1980), the ARFIMA model is more appropriate in capturing long range dependence for modeling persistent. ARFIMA is an extended version of Box-Jenkins(1976) or ARIMA iterative modeling. General formula and parameters for the ARIMA (*p*, *d*, *q*) model is as follows:

$$\Phi\left(B\right)\nabla^{d}X_t = \theta\left(B\right)a_t\,;\ where\ \nabla^{d}X_t = \left(1-B\right)^{d}X_t \quad (14)$$

where Φ and θ are model parameters, B is backshift operator, also called the "backward shift" operator or "lag" operator; here the difference parameter can only take integer value. The general formula for ARFIMA model is similar; the only difference is in parameter d and computational procedure autocorrelation function (PACF). Identification based on sample ACFs and PACFs becomes a highly subjective exercise, as it depends on the skill and experience of the forecaster. In particular, mixed models can be particularly difficult to identify when compared with a pure AR(p) or a pure MA(q) process. For this reason, in recent years information-based criteria such AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion) and others have been preferred and used.

Mayoral (2005) employed AIC in ARFIMA modeling processes and estimated AIC for different values of p, q in the range 0 to 2; the reported results correspond to the preferred model according to lowest AIC. These techniques can help automate the model identification process (the model with lowest criterion is preferred). In this study the AIC method is used to identify most appropriate values for p and q based on the availability of it in OxMetrix6 software. This statistic involves estimating a range of models; the one with the lowest information criterion is selected. These techniques can help automate the model identification process.

Once the preliminary time series model has been identified, the actual model parameter values have to be estimated, using the observation data. The most common methods use maximum likelihood estimation or non-linear least-squares estimation. Floros (2009) estimated different ARFIMA parameters with Maximum Likelihood (ML) estimation using the OxMetrics language (PcGive software).

This paper also employs ML estimation method; this stage carries out a lot of computations, commonly on a computer (using OxMetrix6), to find the best estimates of the parameters of a time-series model. Having chosen a particular ARFIMA model, and having estimated its parameters, this stage includes testing to find whether the chosen model fits the data reasonably well. Some techniques could be used for diagnostic checking: ACF/PACF of residuals, portmanteau test of residuals, normality of error terms and so on. The most important test of the statistical adequacy of a model involves the assumption that the random shocks are independent (residuals are estimated of random shocks). Pan and Chen (2008) indicated that if the model is suitable, residuals should be independently and identically normally distributed; and it could be observed through ACFs of residuals; autocorrelated data usually have significant autocorrelation functions (ACFs) just for small lags. The idea for a sample ACF of residuals is that there are no significant correlations for any lag (not significantly different from zero or lack of a systematic pattern). If there are no significant correlations for any lag, then the random shocks are independent and the model is statistically adequate; otherwise, the iterative process should be started again from the first stage. When all diagnostic checks are satisfied, the model could be used for forecasting.

Data description

This paper focuses on the Philippine exchange rate market, the peso against selected currencies, observing whether the market has an inherent short or long memory. The observation for analysis covers the peso exchange rate versus twenty-two other currencies, as enumerated earlier. For other currencies against the peso there was limited or no historical data for the desired period of study. As has also been stipulated earlier, the analysis covers the last two decades, a 20-year period from 1991 to 2010 except for Euro and UAE which only cover the period of 1999 to 2010, due to data limitation. Data coverage in this period is seamless and has no interruption. The raw data for the time series is comprised of the daily closing prices from the first trading day of January 1991 to the last trading day of December 2010, a range of twenty years. The raw data is secondary data and was obtained from the Bangko Sentral ng Pilipinas website (www.bsp.gov.ph).

Results of classical rescaled range test

Ellis (2007) claimed that in the absence of a bootstrap or Monte Carlo mean for the Hurst exponent, the Anis and Lloyd (1976) and Peters (1994) expected rescaled range may be used to proxy the variable of expected Hurst exponent which exists in the significant test of estimated Hurst exponent. Ellis states that the result of t-equation, which is normalized by standard deviation of expected Hurst exponent, is the equivalent z-statistic for the required level of confidence; that is a significance measure in excess of related t-value derived from t-table; it would indicate, with specific confidence interval, that the observed Hurst exponent is/is not statistically different from its expected value. So if estimated Hurst value would be significantly greater than its expected value, the null hypothesis of no long-term dependence can be rejected. By using the proposed test in methodology, the result of that significant test is reported in Table 2. This table also shows estimated value of Hurst exponent for each currency, and also expected Hurst exponent derived from expected R/S of each individual currency based on the Anis and Lloyd (1976) and the Peters (1994) method.

Table 2

Results for classical rescaled range

	Estimated (H)	Expected (H)	Test result	comment
USD	0.56272	0.52539	2.62	*rejection of the null
TBH	0.46409	0.52539	-4.311	accepting of the null
SGD	0.49618	0.52539	-2.0541	accepting of the null
SAR	0.53146	0.52539	0.4262	accepting of the null
NZD	0.56912	0.52539	3.0752	*rejection of the null
NOK	0.47101	0.52539	-3.8241	accepting of the null
MYR	0.43604	0.52539	-6.2834	accepting of the null
MXN	0.46330	0.52539	-4.3663	accepting of the null
JPY	0.51311	0.52539	-0.86357	accepting of the null
INR	0.54790	0.52539	1.583	accepting of the null
IDR	0.59213	0.52539	4.6933	*rejection of the null
HKD	0.57526	0.52539	3.507	*rejection of the null
GBP	0.54366	0.52539	1.2848	accepting of the null
EUR	0.55320	0.53310	1.495	accepting of the null
DKK	0.52283	0.52539	-0.180	accepting of the null
CHF	0.50754	0.52539	-1.258	accepting of the null
CAD	0.55772	0.52539	2.272	*rejection of the null
BRL	0.57000	0.52539	3.137	*rejection of the null
BND	0.49382	0.52539	-2.2201	accepting of the null
BHD	0.56634	0.52539	2.877	*rejection of the null
AUD	0.49650	0.52539	-2.031	accepting of the null
AED	0.53418	0.53310	0.6181	accepting of the null

Values greater than 1.96 in "test result" column indicate rejection of the null hypothesis or the absence of long-range dependence at the 5% significance level, and the acceptance of the alternative hypothesis of presence of long term memory. This implies that there are only seven out of the twenty-two currencies which reject the null hypothesis of short term memory. These are: USD, CAD, IDR, HKD, BRL, BHD and NZD. The evidence of long-term memory in these exchange rates is weak, because the H values for currencies that showed long-term memory did not exceed 0.59. The interpretation of the Hurst coefficients, even if statistically significant, may not be straightforward and reliable because of various biases brought about by the presence of short-term autocorrelation, the shape of underlying distribution and the Hurst procedure itself. Short-term dependency or autocorrelation has the potential to bias the Hurst coefficient; and the direction and magnitude of the bias depends on the sign and magnitude of the autocorrelation coefficient.

Results of modified rescaled range test

As mentioned in the methodology section of this essay, during the process of modifying the R/S method, one needs to test the significance of $V(q)_n$ to judge whether the series has long memory. This statistic is extremely sensitive to the order of truncation q. If q = 0, Lo's statistic reduces to Hurst's R/S statistic. A small q favors the alternative hypothesis (presence of long memory); and a large q is more in favor of the null hypothesis, making the test somewhat biased. Andrews (1991) provides a data-dependent rule for choosing the optimal lag length q^*. The test is evaluated for that optimal lag orders of $q = q^*$ and also uses the range of q (higher and lower than optimal lag order) to consider values other than

Table 3

V(q) values using modified rescaled range

Lag order	q=0	q=5	q=10	q=15	q=20	q=25	q=30	q=35	q=40	q=optimal	Optimal q
USD	1.579	1.580	1.613	1.567	1.525	1.492	1.482	1.469	1.457	1.6131	10
TBH	0.979	1.194	1.256	1.275	1.296	1.318	1.337	1.350	1.353	1.3094	23
SGD	1.091	1.207	1.267	1.265	1.266	1.262	1.274	1.278	1.272	1.1953	4
SAR	1.349	1.420	1.497	1.476	1.466	1.456	1.455	1.447	1.450	1.4631	22
NZD	1.176	1.285	1.342	1.345	1.356	1.357	1.360	1.349	1.341	1.3584	23
NOK	1.093	1.255	1.308	1.304	1.291	1.292	1.297	1.292	1.286	1.2922	22
MYR	0.864	0.970	1.036	1.072	1.080	1.096	1.111	1.102	1.087	1.0908	23
MXN	0.830	1.224	1.332	1.317	1.311	1.307	1.302	1.303	1.303	1.3110	23
JPY	1.044	1.117	1.138	1.119	1.107	1.100	1.092	1.091	1.086	1.1051	22
INR	1.506	1.513	1.579	1.551	1.532	1.517	1.519	1.512	1.514	1.5601	8
IDR	1.268	1.424	1.483	1.439	1.417	1.403	1.393	1.374	1.360	1.4196	19
HKD	1.464	1.467	1.504	1.455	1.424	1.402	1.395	1.385	1.375	1.4168	22
GBP	1.486	1.518	1.545	1.517	1.493	1.476	1.465	1.453	1.443	1.4872	22
EUR	1.517	1.656	1.676	1.654	1.625	1.612	1.610	1.606	1.615	1.6565	5
DKK	1.278	1.371	1.409	1.384	1.359	1.343	1.338	1.334	1.330	1.3465	3
CHF	1.169	1.216	1.170	1.206	1.188	1.175	1.173	1.173	1.169	1.1852	21
CAD	1.442	1.503	1.567	1.534	1.532	1.527	1.534	1.529	1.523	1.5392	14
BRL	1.430	1.498	1.496	1.445	1.418	1.392	1.376	1.360	1.348	1.4123	21
BND	1.058	1.203	1.270	1.268	1.268	1.266	1.279	1.283	1.277	1.2026	5
BHD	1.586	1.563	1.620	1.561	1.522	1.495	1.488	1.478	1.470	1.5127	22
AUD	0.914	1.013	1.050	1.044	1.041	1.036	1.031	1.027	1.024	1.0380	23
AED	1.686	1.553	1.554	1.518	1.490	1.472	1.462	1.453	1.437	1.5534	5

optimal lag order q = 0, 5, 10, 15, 20, 25, 30, 35 and 40 in excess of optimal lag. The results from analysis of the modified R/S statistic are reported in Table 3. For all exchange rates time series, the null hypothesis of short-memory is not rejected at any lag order. Surprisingly, all exchange rates do not have long memory since the test results for different lags fall in the acceptance region and did not exceed interval levels, in contrast to the results of classical rescaled range.

The null hypothesis of no long memory cannot be rejected at the 5% and 1% significance level for all exchange rates. Overall, the modified rescaled range statistic results support the null hypothesis of no long-term dependence in the whole sample of all exchange rate time series for the specified period.

Results of rescaled variance test

There is more support for the absence of long memory in real exchange rates when one shifts to Table 4. In Table 4, the V/S statistic results are reported. One may consider the same truncation lag of q similar to the modified rescaled range for having a fair comparison between these two methods. There is again no evidence of long memory in all exchange rates; and the null hypothesis cannot be rejected for all series returns and for each lag order. The results fall in line with those reported by the modified R/S analysis, since both tests were not able to reject the null hypothesis of short memory.

Table 4

V/S statistics results for rescaled variance test

Lag order	q=0	q=5	q=10	q=15	q=20	q=25	q=30	q=35	q=40	$q= q^*$	Optimal $q(q^*)$
USD	0.1785	0.1788	0.1864	0.1759	0.1666	0.1595	0.1573	0.1546	0.1520	0.1864	10
TBH	0.0236	0.0351	0.0388	0.0400	0.0414	0.0428	0.0440	0.0449	0.0451	0.0422	23
SGD	0.0584	0.0714	0.0788	0.0785	0.0786	0.0781	0.0796	0.0801	0.0794	0.0701	4
SAR	0.1404	0.1555	0.1728	0.1681	0.1659	0.1635	0.1634	0.1616	0.1621	0.1651	22
NZD	0.0713	0.0852	0.0929	0.0933	0.0948	0.0951	0.0954	0.0939	0.0928	0.0952	23
NOK	0.0716	0.0944	0.1025	0.1019	0.0999	0.1000	0.1008	0.1000	0.0991	0.1001	22
MYR	0.0366	0.0462	0.0526	0.0563	0.0572	0.0589	0.0605	0.0595	0.0579	0.0584	23
MXN	0.0512	0.1114	0.1318	0.1288	0.1276	0.1270	0.1260	0.1262	0.1261	0.1277	23
JPY	0.0474	0.0542	0.0562	0.0544	0.0533	0.0525	0.0519	0.0517	0.0512	0.0531	22
INR	0.1656	0.1673	0.1821	0.1756	0.1714	0.1680	0.1684	0.1669	0.1673	0.1777	8
IDR	0.0432	0.0544	0.0590	0.0556	0.0539	0.0529	0.0521	0.0507	0.0497	0.0541	19
HKD	0.1704	0.1710	0.1798	0.1682	0.1613	0.1562	0.1548	0.1526	0.1502	0.1596	22
GBP	0.1693	0.1767	0.1829	0.1764	0.1709	0.1669	0.1646	0.1618	0.1595	0.1695	22
EUR	0.1246	0.1486	0.1521	0.1482	0.1430	0.1407	0.1404	0.1397	0.1413	0.1486	5
DKK	0.0947	0.1090	0.1151	0.1111	0.1070	0.1045	0.1038	0.1031	0.1026	0.1051	3
CHF	0.0616	0.0667	0.0681	0.0655	0.0636	0.0623	0.0620	0.0620	0.0616	0.0633	21
CAD	0.1380	0.1500	0.1630	0.1563	0.1558	0.1549	0.1563	0.1551	0.1540	0.1573	14
BRL	0.0565	0.0620	0.0618	0.0577	0.0555	0.0535	0.0523	0.0511	0.0502	0.0551	21
BND	0.0546	0.0705	0.0786	0.0784	0.0784	0.0781	0.0797	0.0802	0.0795	0.0705	5
BHD	0.1763	0.1711	0.1839	0.1707	0.1624	0.1565	0.1552	0.1531	0.1514	0.1603	22
AUD	0.0441	0.0542	0.0582	0.0576	0.0572	0.0566	0.0562	0.0557	0.0554	0.0569	23
AED	0.1862	0.1582	0.1583	0.1510	0.1454	0.1420	0.1402	0.1383	0.1353	0.1582	5

The following must be noted:

The table tabulates the rescaled variance statistics $M(q)_N$ as suggested by Giraitis et al. (2003), which analyzed returns of selected exchange rates for long-term memory detection. The confidence limit for V/S test is 0.1869 which indicates significance at 5% and 0.2685 which indicates significance at 1% level for the null hypothesis of a short-memory process. At the 5% or 1% significance level, the null hypothesis of a short-memory process is rejected if the V/S test result exceeds the respective confidence limit. By comparison among the results from three Analysis Methods of Long Memory, it appears that when considering the results from the three tests, there is overwhelming evidence supporting the absence of long memory in exchange rates. Although some evidence of long-term dependence is found (by using conventional rescaled method) in some exchange rate returns for respective sample period, it is not convincing because it could be due to low-order or short-term dependence in that particular series. On the other hand, modified R/S and V/S statistics are not affected by short-term dependency and has reasonable power against a long-term dependent process. Hence, the Hurst test might incorrectly lead to a rejection of the null hypothesis of short term memory.

ARFIMA modeling result:

The existence of long-term memory was rejected for all currencies, using two reliable methods, the modified rescaled range of Lo (1991) and the rescaled variance method of Giraitis et al. (2003). Therefore, these models suggest that ARFIMA modeling is not a good tool for modeling these time series. But by using the classical rescaled range method, the results of Hurst exponent of seven currencies showed long-term memory. Parameter d in ARFIMA models can be fractional; several techniques have been proposed to estimate the fractional differencing parameter d. Here two methods are employed: First, the method proposed by Hosking (1980), and Peters (1994). **They** proposed and proved that the link between the self-similarity parameter or Hurst exponent of FGN and the ARFIMA parameter d is that $H = d + ½$; the finding obtained this relation between H and d by using the behavior of their spectral densities. The second method is estimating fractional differencing parameter d by using Whittle's method (Approximate Maximum Likelihood Method), because the study results of Reisen et al.(2001) implied that the Whittle's method for estimating d is more accurate than the other methods. In Table 5 below, estimation for fractional differencing parameter d, based on two mentioned methods, are reported.

Table 5

Estimating of d

Currency	H	d = H - 1/2	Whittle Estimator output (test statistic)		
			z-score	p-value	Estimated d
BHD	0.56634	**0.06634**	2.18029	0.0292	**0.085386**
BRL	0.57000	**0.07000**	2.00558	0.0449	**0.083277**
CAD	0.55772	**0.05772**	0.950903	0.3417	**0.03724**
HKD	0.57526	**0.07526**	1.93575	0.0529	**0.07581**
IDR	0.59213	**0.09213**	1.25489	0.2095	**0.049145**
NZD	0.56912	**0.06912**	1.06286	0.2878	**0.041625**
USD	0.56272	**0.06272**	2.63857	0.0083	**0.10333**

*Local *Whittle* estimation *method procedure is done by GRETL software, and in test output the z-value and p-value of test are reported with estimated d.*

Based on the results of Whittle's method and p-values for estimation of parameter d, it could be observed that the value of parameter d is only significant for three currencies, namely, BHD, BRL and USD. The others are not significantly different from zero because of no long-term memory or very weak evidence of it. The results derived from Hosking (1980) methods also have small value of parameter d; according to Xiu et al.(2007), if fractional differencing parameter d will be small, it will cause difficulty in observing the effect of the fractional differencing methods, and consequently in model fitting. Besides, this method is based on H value which is a biased measure of long term memory and is disputable. So, only the significant d values for three currencies based on Whittle's method will be considered for ARFIMA(p,d,q) modeling of three exchange rates: BHD, BRL and USD.

In the ARFIMA (p,d,q) modeling for selected currencies, the value of differencing parameter or d is constant and is equal to what is obtained in Whittle's method estimation. The model could be written as: ARFIMA(p,0.085,q), ARFIMA(p,0.083,q) and ARFIMA(p,0.1,q) for BHD, BRL and USD ,respectively. In order to complete our modeling, the value for p and q for each model should be estimated. Commonly, the greater value than 2 for combination of p and q would lead to insignificant parameter estimation; so, only the value of 0,1,2 for p and q will be considered for parameter estimation. (Higher orders of *p* and *q* were also performed, but most of the models were inappropriate in view of insignificant parameters.) To find that which is the most appropriate value of p and q to use in the modeling, all possible combinations that could exist (based on the p,d,q values) would be examined in ARFIMA (p,d,q) model. In this case, there are nine combinations for each currency which are listed in Table 6. The AIC (Akaike Information Criterion) is used for comparative analysis among many models so as to choose the appropriate one with lesser value of AIC, in order to pick the right value for p and q. This technique can help automate the model identification process. It requires computer software; here OxMetrix6 is used to find AIC for each model which is shown in Table 6 below.

Table 6

Estimating the value of AIC

BHD d= 0.085	**AIC**	**BRL d=0.083**	**AIC**	**USD d=1.033**	**AIC**
ARFIMA(0,d,0)	-37350.4806	ARFIMA(0,d,0)	-24569.818	ARFIMA(0,d,0)	-36906.7655
ARFIMA(0,d,1)	-37364.8478	ARFIMA(0,d,1)	-24628.8489	ARFIMA(0,d,1)	-36904.6999
ARFIMA(0,d,2)	-37422.2194	ARFIMA(0,d,2)	-24631.7744	ARFIMA(0,d,2)	-36967.107
ARFIMA(1,d,0)	-37361.1513	ARFIMA(1,d,0)	-24624.6911	ARFIMA(1,d,0)	-36905.4721
ARFIMA(1,d,1)	-37376.2477	ARFIMA(1,d,1)	-24640.4549	ARFIMA(1,d,1)	-36910.253
ARFIMA(1,d,2)	-37377.9688	ARFIMA(1,d,2)	-24639.9685	ARFIMA(1,d,2)	-37015.726
ARFIMA(2,d,0)	-37431.1961	ARFIMA(2,d,0)	-24626.8165	ARFIMA(2,d,0)	-36962.4904
ARFIMA(2,d,1)	**-37471.7789**	ARFIMA(2,d,1)	-24640.2617	**ARFIMA(2,d,1)**	**-37020.7303**
ARFIMA(2,d,2)	-37469.8155	**ARFIMA(2,d,2)**	**-24654.6524**	ARFIMA(2,d,2)	-37020.0693

The OxMetrix6 software was used to find AIC (Akaike Information Criterion) for all combination models, reported in Table 6. The lowest AIC for each currency is highlighted in the table; so, ARFIMA(2,0.085,1), ARFIMA(2,0.083,2) and ARFIMA(2,0.103,1) are chosen for BHD, BRL and USD, respectively. The next step is to find the estimation of the parameters or coefficient of the selected ARFIMA model. The estimation stage begins with computing the parameters θ and φ in a main formula. If the estimated coefficients would be insignificant, the model that has the second lowest AIC should be examined until the model with significant coefficients is found. Based on the software output for estimating the model, the coefficients of ARFIMA(2,0.085,1) model for BHD and ARFIMA(2,0.103,1) model for USD are significant, but one of the coefficient in ARFIMA(2,0.083,2) model for BRL is insignificant; so, the second lowest AIC model for this currency should be examined for coefficient estimation. The second lowest AIC model for BRL based on Table 6 is ARFIMA(1,0.083,1). Now the coefficients of ARFIMA(1,0.083,1) model for BRL are significant; this model could be a better choice.

Having chosen ARFIMA models, and having estimated their parameters, the next step includes testing to find out whether the chosen model fits the data reasonably well. The ARFIMA model with the estimated coefficients is checked and tested to determine if the estimated model is statistically adequate or not (i.e. diagnostic checking). The most important test of the statistical adequacy of a model involves the assumption that the random shocks are independent. It can be tested through ACF of residuals. If there are no significant correlations for any lag, then the random shocks are independent and the model is deemed statistically adequate; otherwise, it is not adequate. Therefore the ACF of residuals for the three currencies are examined. No significant spike in ACF is found and all correlations lie between the two boundaries (see Appendix 4). So ARFIMA(2,0.085,1), ARFIMA(1,0.083,1) and ARFIMA(2,0.103,1) could be used for the modeling of BHD, BRL and USD currencies, respectively. When the diagnostic checks are satisfied, the model could be used for forecasting. This stage can provide points and confidence intervals (error band) for predetermined future period.

Software-Based Tool development

The software-based financial tools for automating the procedures of modified rescaled range statistic computation based on Andrew Lo's (1991) methodology and rescaled variance statistics based on the Giraitis et al.(2003) methodology are developed. It aims to ease the process of computation the existence of long-range dependence in the financial market time series dataset. This software-based tool should compute the value of $V(q)_N$ for modified rescaled range by using the formula below;

$$V(q)_N \equiv \frac{[\underset{1\le k\le N}{Max}\sum_{j=1}^{k}(X_j-\overline{X}_N)-\underset{1\le k\le N}{Min}\sum_{j=1}^{k}(X_j-\overline{X}_N)]}{\sqrt{N}(\frac{1}{N}\sum_{j=1}^{N}(X_j-\overline{X}_N)^2+\frac{2}{N}\sum_{j=1}^{q}(1-\frac{j}{q+1})[\sum_{i=j+1}^{N}(X_i-\overline{X}_N)(X_{i-j}-\overline{X}_N)])^{1/2}}$$

This paper provides and develops software-based tools which can be deployed in two deferent software; MATLAB and Excel. The provided file for Excel is an add-in for PC versions of Microsoft Excel (version 97 and up) that helps with the computation of Lo's (1991) modified rescaled range statistic models and ends up finding out if a time-series has long-range dependency or short-range dependency . It was originally written to analyze the Philippine foreign exchange market in terms of examining for the presence of long term memory in exchange rate returns for the respective time-series. But it has a much broader application and could be used for any time-series to study long-range dependency. This paper also provides and develops the software-based tool for rescaled variance statistics which can be deployed in two deferent software; MATLAB and Excel. The software-based tool for rescaled variance statistics should compute the value of $M(q)_N$ by using the formula below:

$$M(q)_N \equiv \frac{[Var(S_1^*, \cdots, S_N^*)]}{N(\frac{1}{N}\sum_{j=1}^{N}(X_j - \overline{X}_N)^2 + \frac{2}{N}\sum_{j=1}^{q}(1 - \frac{j}{q+1})[\sum_{i=j+1}^{N}(X_i - \overline{X}_N)(X_{i-j} - \overline{X}_N)])}$$

Excel users can conduct these two tests after installation in two different ways: first, by using insert function and selecting MRS and RVS functions under user defined functions (UDF) menu; and second, by using provided Excel templates included in the software package. In order to make the tools and their related functions more user-friendly, one Excel template for each tool is provided in the software package. In these templates the user should just paste or enter the time series of closing price and "q" to see the result, without entering any specific formula. The result for rejection or accepting the null hypothesis will also be shown after entering the inputs. There is also a table for different value of "q" for comparative purposes. These two templates must be used after installing all needed files and add-ins. The snapshots of these two different implementations of the tool are provided in Appendix 1.

MATLAB users can apply the two tests for long-term memory by using MATLAB codes which are available in Appendix 2 and 3; or they can use the MATLAB files in the software package. The software package, including the MATLAB files and Excel add-ins for both methods, and also the user's guide documents, can be downloaded from this website: http://www.mediafire.com/?712usp7x2p970te

CONCLUSION

The debate over the use of fractional Brownian motion is raging in the quantitative finance community. As finite data sets created using Brownian motion will always give a value of the Hurst exponent larger than 0.5, this value can therefore mistakenly be interpreted as evidence of long term memory; and one may need an appropriate statistical test to judge its significance. However, the results are not convincing when using a conventional test like the classical R/S analysis of the Hurst (1951), although some evidences of long-term dependence are found in some exchange rate returns for a respective sample period, However this finding was not supported when the Lo (1991) and the Giraitis et al. (2003) procedures were applied to the same markets. Hence, the modified R/S analysis and the V/S test were used to minimize short-term dependence in this study. The results from the modified R/S statistics cannot reject the null hypothesis of short-term dependence in all exchange rate returns. In addition to the modified R/S statistics, the results from the V/S test suggest that there is no evidence of long-term dependence in all exchange rate returns. This indicates that exchange rate returns are a short-term dependence process or random walk, corresponding to the assumption of the EMH.

The study results suggest that the significant Hurst (1951) result identified in some of the exchange rates was due to low-order or short-term dependence in that particular series. Thus, in line with Fama's (1998) suggestion that long-term anomalies may be due to "methodological illusions", it could be explained that rejection of the random null hypothesis in some exchange rates in the classical rescaled range method could be conditional on both the procedure used and the period being tested. Lo's statistic is not affected by short-term dependency and has reasonable power against a long-term dependent process. However, Lo's test and rescaled variance test are more appropriate approaches to the data in this study. In general, the study does not find strong support for long-term memory in the exchange rates changes process of the selected currencies series during the period of 1991 to 2010.

There could be various reasons for the evidence of long-term memory which was found in many previous studies; but the test statistics applied in this study (modified R/S and V/S statistic) , and not just the use of the classical rescaled range, could be more appropriate for the data being analyzed. Another factor might be using longer, broader and more recent samples to provide more reliable statistical inferences. Another explanation could be the increased sophistication of the market participants. As the currency market matures and the understanding of the determinants of exchange rates improves, most relevant information is rapidly reflected in the prices. The increased flow of information resulting from technological advances also helps this process. The proponent believes that the major contribution of this paper is to provide evidence that conclusions on long-term memory in exchange rates are dependent on or sensitive to the method of analysis chosen by the researcher. As a consequence, the statement on empirical knowledge of long-term processes is not as strong as previously believed.

This absence of dependence in currency markets is consistent with informational efficiency and the inability to capture abnormal returns from long-cycle patterns. Most financial models assume that asset prices follow a random walk ,and most financial models are based on the assumption of absence of predictability. Having no long-term memory indicates random walk and a market efficiency hypothesis which is precisely the theoretical base of the Capital Asset Pricing Model (CAPM), the Arbitrage Pricing Theory (APT), the Black & Scholes model and the Modern Portfolio Theory (MPT).

BIBLIOGRAPHY

Ahking, W. (2010). Non-parametric tests of real exchange rates in the post-Bretton Woods era Francis. *Empirical Economics, 39*(2), 439-456.

Alptekin, N. (2006). Long memory analysis of USD/TRL exchange rate. *International Journal of Social Sciences*, *1*(2),111-116.

Andrews, D.W.K. (1991). Hetroskedasticity and the autocorrelation consistent covariance matrix estimation. *Econometrica*, *59*(3), 817-858.

Anis, A., & Lloyd, E. (1976). The expected value of the adjusted rescaled Hurst range of independent normal summands. *Biometrika, 63*, 111–116.

Assaf, A. (2004). Rescaled variance analysis of real exchange rates. *Applied Economics Letters*, *11*, 303-306.

Assaf, A. (2008). Long memory in international equity markets: revisited. *Applied Financial Economics Letters*, *4*, 433–437.

Batten, J., Ellis, C., & Fetherston, T.A. (2000). Are long-term return anomalies illusions: evidence from the spot yen. *Japan and World Economy, 12* (4, December 2000), 337-349.

Bhardwaj, G., & Swanson, N. R. (2006). An empirical investigation of the usefulness of ARFIMA models for predicting macroeconomic and financial time series. *Journal of Econometrics, 131*,539-578 .

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: forecasting and control*. San Francisco, CA: Holden-Day, 575 pp.

Cannon, M. J., Percival, D. B., Caccia, D. C., Raymond, G. M., & Bassingthwaighte, J. B. (1997). Evaluating scaled windowed variance methods for estimating the Hurst coefficient of time series. *Physica A, 241*, 606–626.

Caporale, G.M., & Gil-Alana, L.A. (2009). Long Memory in US Real Output per Capita. CESifo Group Munich, *CESifo Working Paper Series No.* 2671.

Doornik, J. A., & Hendry, D. F. (2007). Empirical Econometric Modeling using PcGive 12, *Timberlake Consultants Ltd, London, Vol 4,* 220-236.

Ellis, C. (2007). The Sampling Properties of Hurst Exponent Estimates. *Physica A, 375*, 159-173.

Fama, E.F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics 49*, 283-306.

Floros, C. (2009). Long memory in milk prices: evidence from EU-15. *International Journal of Applied Economics, 6,* 10-20

Giraitis, L., Kokoszka, P., Leipus, R., & Teyssière, G. (2003). Rescaled variance and related tests for long memory in volatility and level. *Journal of Econometrics, 112*, 265-294 .

Joyeux, R., & Granger C.W.J. (1980). An introduction to long-memory time series models and fractional differencing. *J. Time Series Anal*, 15–29.

Hosking, J.R.M. (1980). The multivariate portmanteau statistic. *Journal of American Statistical Association, 75,* 602-607.

Hosking, JRM. (1996) Asymptotic distributions of the sample mean, autocovariances and autocorrelations of long-memory time series. *Journal of Econometrics, 73,* 261-284.

Hurst, H. (1951). Long-term storage capacity of reservoirs. *Transactions of the American Society of Civil Engineers, 116,* 770−808.

León, C., & Reveiz, A. (2010). Portfolio optimization and long-term dependence. *Borradorse De Economia 007487*.

Lo, A.W. (1991). Long term memory in stock market prices. *Econometrica, 59,* 1279-1313.

Mandelbrot, B.B. (1969). Long-run linearity, locally Gaussian processes. H-spectra and infinite variances. *International Economic Review, 10*, 82-111.

Mayoral, L. (2005). *A new minimum distance estimator for ARFIMA processes*. Working Paper, Universitat Pompeu Fabra.

Mukherjee, I., Sen,, C. & Sarkar A. (2011). Long memory in stock returns: Insights from the Indian market. *Applied Econ, Finance, 5,* 62-74.

Newey, W., & West, K. (1987). A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55,* 703-708.

Pan, J.N., & Chen, S.T. (2008). Monitoring long-memory air quality data using ARFIMA model. *Environmentics, 19,* 209-219.

Peters, E.E. (1994). *Fractal market analysis: applying Chaos Theory to investment and economics*. New York: Wiley Finance Editions.

Reisen V.A, Abraham, B., Lopes, S.R.C. (2001). Estimation of parameters in ARFIMA processes: a simulation study. *Commun. Stat. Simulation Comput, 30*, 787–803

Teverovsky, V., Taqqu, M.S., & Willinger, W. (1999). A critical look at Lo's modified R/S statistic. *J. Stat. Plann. Inference, 80,* 211–227.

Willinger, W., Taqqu, M.S., &Teverovsky, V. (1999). Stock market prices and long-range dependence. *Finance Stochastics, 3,* 1-13

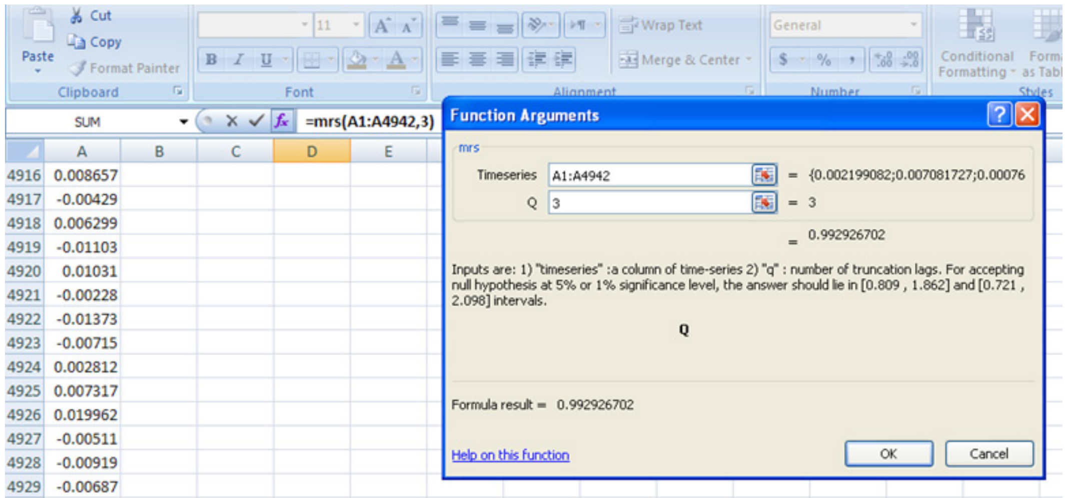
Whittle, P. (1953). The analysis of multiple stationary time series. *Statist. Soc. B, 15,* 125–139.

Xiu, J., & Jin, Y. (2007). Empirical study of ARFIMA model based on fractional differencing. *Physica A377*, 138-154.

* Notes: the table consolidates the modified rescale range statistics V(q) as suggested by Lo (1991), which examined returns of selected exchange rates for long-term memory detection. The confidence interval for modified R/S is [0.809, 1.862] which indicates significance at 5%, and [0.721, 2.098] which indicates significance at 1%level for the null hypothesis of a short-memory process. At the 5% or 1% significance level, the null hypothesis of a short-memory process is rejected if the modified R/S statistic does not fall within the respective confidence intervals .

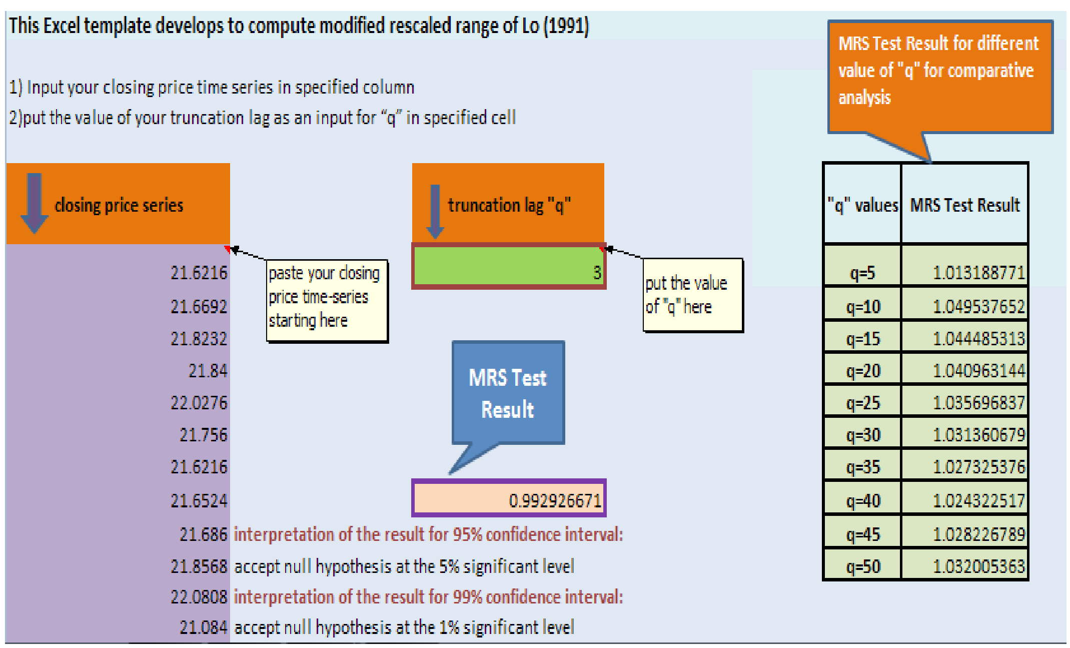
Appendix 1

1: *Snapshot of "MRS.xla" (Excel add-in) for predetermined inputs:*



2: *Snapshot of Excel template (related to modified rescaled range) for predetermined inputs:*

.



- In order to make the tools and their related functions more user-friendly, one Excel template for each tool is provided in the software package (namely: "Excel template for MRS.xlsx" and "Excel template for RVS.xlsx"). In these templates, a snapshot of which are shown above, the user should just paste or enter the time series of closing price and "q" to see the result without entering any specific formula. The result for rejection or accepting the null hypothesis will also be shown after entering the inputs. There is also a table for different value of "q" for comparative purpose. These two templates must be used after installing all needed files and add-ins previously mentioned

Appendix 2

MATLAB codes for Lo's (1991) rescaled range:

The following generic codes are also available in one file (MRS.m) which is included in the software package. It is designed to test long/short dependency of a series based on the modified rescaled range of Lo (1991). The inputs are: 1) time series of market closing price; and, 2) truncation value which is denoted by q. The output is the test result.

MATLAB codes:

```
function vtest = MRS(timeseries,q)
n=length(timeseries);
A=timeseries(2:n);
B=timeseries(1:(n-1));
timeseriesreturn=log(A)-log(B);
n2=length(timeseriesreturn);
Mu=mean(timeseriesreturn);
deviation=cumsum(timeseriesreturn-Mu);
numerator=max(deviation)-min(deviation);
if q==0
denominator=std(timeseriesreturn,1;
vtest=(1/sqrt(n2))*(numerator/denominator);
else
for j=1:q
omega(j,1)=(1-(j/(q+1)));
end
autocovariance=xcov(timeseriesreturn,'
biased');
N=length(autocovariance);
firstqautocov=autocovariance
((n2+1): N,1);
qautocov=firstqautocov(1:q,1);
denominator=sqrt(var(timeseriesreturn,1) +2*sum(omega.*qautocov));
vtest =(1/sqrt(n2))*(numerator/denominator);
end
if (vtest > 1.862) && (vtest <= 2.098);
display('null hypothsis rejected at the 5% level of significance');
elseif (vtest > 2.098);
display('null hypothsis rejected at the 1% level of significance');
else
display('accepting null hypothsis at 5% significant level');
end
```

Appendix 3

MATLAB codes for Giraitis et al. (2003) rescaled variance (V/S):

The following generic codes are also available in one file (RVS.m) which is included in the software package. It is designed to test long/short dependency of a series based on the rescaled variance statistics of Giraitis et al. (2003). The inputs are: 1) time series of market closing price; and, 2) truncation value which is denoted by q. The output is the rescaled variance test result.

MATLAB codes:

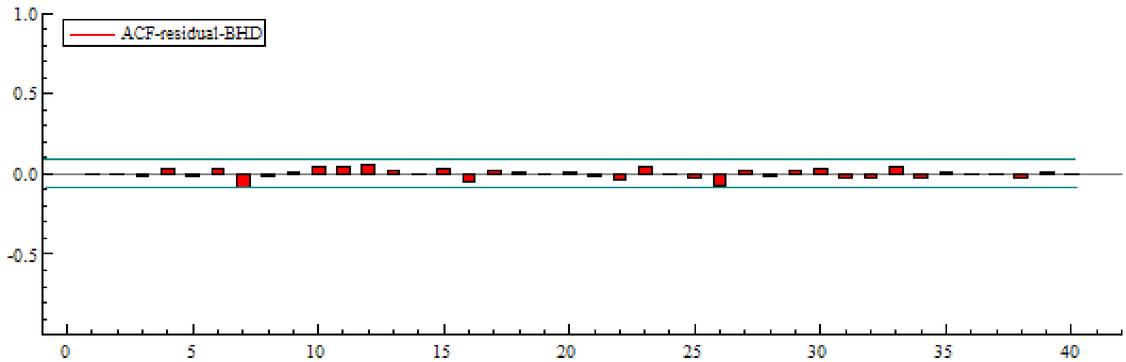
```
function vs = RVS(timeseries,q)
n=length(timeseries);
A=timeseries(2:n);
B=timeseries(1:(n-1));
timeseriesreturn=log(A)-log(B);
n2=length(timeseriesreturn);
Mu=mean(timeseriesreturn);
deviation=cumsum(timeseriesreturn-Mu);
numerator=var(deviation);
if q==0
denominator=var(timeseriesreturn,1);
vs=(1/n2)*(numerator/denominator);
else
for j=1:q
w(j,1)=(1-(j/(q+1)));
end
autocovariance=xcov(timeseriesreturn,’ biased’);
N=length(autocovariance);
firstqautocov=autocovariance((n2+1): N,1);
qautocov=firstqautocov(1:q,1);
denominator=(var(timeseriesreturn,1)+ 2*sum(w.*qautocov));
vs = (1/n2)*(numerator/denominator);
end
if (vs > 0.1869) && (vs<=0.2685);
display(‘null hypothsis rejected at the 5% level of significance’);
elseif (vs > 0.2685);
display(‘null hypothsis rejected at the  1% level of significance’);
else
display(‘accepting null hypothsis at 5%      significant level’);
end
```

Appendix 4

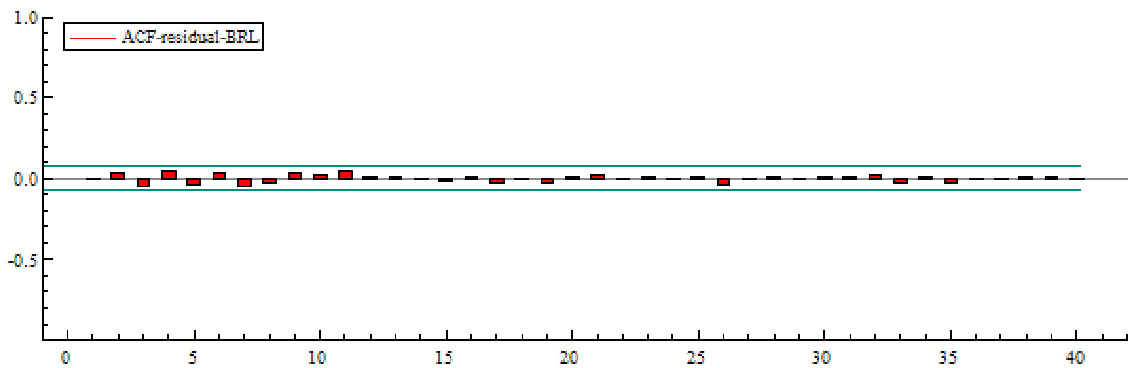
The output of OxMetrix6 software for ACF of residuals (residual autocorrelation)

The ARFIMA models with the estimated coefficients for the three currencies are examined; and results for ACF of residuals are as follows:

ACF of residuals(BHD):



ACF of residuals (BRL):



ACF of residuals (USD):