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Testing for Random Walk in African Foreign Exchange Markets: Evidence from Multiple Variance Ratio Tests

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Abstract

This paper examines the random walk hypothesis for thirteen African foreign exchange markets.The hypothesis is tested with variance ratio tests based on power transformation,wild bootstap and multiple ranks from daily and weekly data. The use of a battery of recent joint variance ratio tests provide further evidences against the random walk behavior than the conventional variance ratio test. The iid hypothesis is rejected in all 13 markets. In four African exchange currency markets, Egypt, Kenya, South-Africa and Zambia, daily returns are a martingale difference sequence. Extreme values are important factors which contribute to whether exchange rates follow random walk.

Keywords: Exchange Market Efficiency,Random Walk, Dollar Exchange rates, Variance Ratio Test.

1. Introduction

With increasing globalisation, nations are exposed to international community, and trading in both goods and services will be affected to a large extent by moviments in exchange rates. For instance, an appreciation of local currency results in loss of national competiveness as export become more expensive and trading partners switch to relative cheaper sources. At the same time, traders benefit since imports become cheaper. Many studies have been carried out to test the financial markets efficiency ever the seminal by Fama (1970). Apart from stocks and equities, foreign-exchange is a key component of the financial sector. Testing for random walk hypotesis (here after RWH) in exchange rates is of interest to all parties including academics, practitioners and regulators because it provides a benchmark for evaluating the perfomance of alternative models of exchange rates determination.While academicians seek to understand the behavior of asset returns over time, practitioners and investors are often interested in identifying market inefficiency that produce exploitable patterns in exchange rate returns. Regulators in contrast, are interested in improving the informational efficiency of the security market in which exchange rate are traded Belaire-Franch and Opong (2005).

Since the seminal work of Lo and Mackinlay (1988, 1989) and Poterba and Summers (1988), a number of reseachers has been devoted their efforts to examine the random walk behavior of currency returns and attempted to apply the variance ratio [VR thereafter] test to different markets throughout the world. Among others the litterature recognizes: Liu and He (1991), Urrutia (1995), Ayaji and karemera (1996), Fong *et al*.(1997), Wright (2000), Lee *et al*.(2001), Yilmaz (2003), Belaire-Franch and Opong (2005), Lima and Tabak (2007), Charles and Darné (2009) and Firoj and Khanom (2018). The findings are mixed depending of the different markets, frequency, time period and methodologies employed in the previous studies. For example, Liu and He (1991) applied variance ratio tests based on Lo and Mackinlay (1988) and provided evidence that rejected the RWH for German mark, Japanese yen and British pound, but failed to reject for the Canadian dollar and French franc vis-à-vis the US dollar. Their results suggest that autocorrelations are presented in weekly increments nominal exchange rate returns. Fong *et al*. (1997),Wright (2000), Yilmaz (2003) and Chang (2004) reexamined the same five exchange rates using various VR tests. Ayaji and Karemera (1996), Lee et al.(2001), Lima and Tabak (2007) and Azad (2009) analyzed foreign exchange rates of Asian countries (Hong Kong dollar, Indonesian rupiah, Korea won, Malaysian ringgit, Philippine peso, Singaporean dollar, Taiwanese dollar and Thai baht).

From the literature, it is clear that the issue of currency returns has not received adequate attention in the context of African countries. Financial markets in developing countries tend to be underdevelopped and inefficient, unlike those in industrialized countries. This implies that the dynamics which govern currency returns for developed countries are unarguarbly different from those associate with developping countries, where financial markets are inefficient.In addition when african markets are studied, authors concentrate in general, on stocks and equities market, see Gyamphi (2018) and Smith (2008) among others. Contrarily to the previous studies that focused attention mainly on the random walk behavior of currency returns of industrialised countries and the african stocks markets, the present study attempts to broaden our understanding of this issue by extending the debate to African currency markets. To the best of our kwnoledge, Al-Khazali and Koumanakos (2006), Mbululu*et al*.(2013) and Onoruo and Braha (2015) are among the few studies that used VR to evaluate RWH of currency returns for African countries. However, examining whether or not currency returns exhibit a random walk behavior should be important to investors who seek to exploit the opportunities created by inefficiencies in foreign exchange markets.

The purpose of this article is to carry out a rigorous tests of random walk hypothesis for 13 African currency markets. Individual and joint variance ratio tests of random walk hypothesis are used to examine two variants: (i) the conventional iid random walk and (ii) a less restrictive version which allows for conditional heteroscedasticity in exchange rate returns and so tests the hypothesis, that returns are a martingale difference sequence (mds). If an asset price follows a martingale, then its return is purely unpredictable and investors are unable to make abnormal returns overtime. Hence, the question as to whether an exchange rate price follows a martingale has strong implications in weak-form of the efficient market hypothesis, which implies the random walk. The particular tests employed are development of Lo and Mackinlay's (1988) variance approach. They are based on ranks and signs (see Wright,2000), wild bootstrapping and the power transforming of Chen and Deo (2006). Kim and Shamsuddin (2008) showed that wild bootstrap is robust to structural changes and extreme values and Chen and Deo (2006) variance ratio test by power transformation correct a well-known problem with the variance ratio test, namely that the variance ratio statistic is biased and right skewed in finite samples. We study both daily and weekly data for some African currency rates over the period 2000-2017. Following Azad (2009), we analyze the weak-form of the efficient market hypothesis using both daily and weekly because a market can be considered to be perfectly weak-form efficient if it is found to behave randomly at any level of data frequency. The paper finds that four markets show weak-form efficiency while the remaining currency markets are found inefficient.

The rest of the article is organized as follows: Section 2 discuss the different variance ratio tests. Section 3 summarises the characteristics of the data and reports the empirical results. Section 4 provides a (brief) conclusion.

2. Methodologies: Variance Ratio Tests

Variance ratio tests are particularly useful for examining the behavior of asset price because they do not assume returns are normally distributed and permit a general forms of heteroscedasticity. They are based on the fact that if returns are uncorrelated the variance of the k-period return is $k$times the variance of one period return; Lo and MacKinlay[LOMAC, thereafter](1988) derived two statistics for testing (i) whether asset prices follow an iid random walk and (ii) whether returns form a martingale difference sequence (mds), respectively.

Consider the random walk with drift model,

$$p_t = \mu + p_{t-1} + \varepsilon_t \; or \; y_t = \mu + \varepsilon_t \tag{1}$$

Where μ is a drift parameter and $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_{t-g}) = g \neq 0$ for all t.With the conventional random walk, the $\{\varepsilon_t\}$ are iid and so any conditional heteroscedasticity is excluded.

Given a times series of asset returns y_t, with $t = 1, \dots, T$. The variance ratio using overlapping k^{th} differences is given by

$$VR(k) = \left\{\frac{1}{Tk}\sum_{t=k}^{T}(y_t + y_{t-1} + \cdots + y_{t-k+1} - k\hat{\mu})^2\right\} \div \left\{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{\mu})^2\right\} \tag{2}$$

where

$$\hat{\mu} = \frac{1}{T}\sum_{t=1}^{T} y_t$$

and with uncorrelated returns $VR(k) = 1$. Time series is said to be mean-reverting if $VR(k)$ is significantly lower than the unity at long horizons k. However, time series are mean-averting i.e. explosive if $VR(k)$ is significantly higher that unity at long horizons. Lo and Mackinlay (1988) showed that under an iid random walk, the statistic test

$$M_1(k) = [VR(k) - 1]\left[\frac{2(2k-1)(k-1)}{3kT}\right]^{\frac{1}{2}} \tag{3}$$

is asymptotically distributed as standard normal. Under their assumption H^* in which returns innovations have zero mean, are uncorrelated at all leads and lags, while allowing for general form of heteroscedasticity, they showed that the test statistic

$$M_2(k) = [VR(k) - 1]\left[4\sum_{j=1}^{k-1}\left(1 - \frac{j}{k}\right)^2 \delta_j\right]^{-\frac{1}{2}} \tag{4}$$

where

$$\delta_j = \left[\sum_{t=j+1}^{T}(y_t - \hat{\mu})^2 (y_{t-j} - \hat{\mu})^2\right] \div \left[\left(\sum_{t=1}^{T}(y_t - \hat{\mu})^2\right)^2\right]$$

is asymptotically normal.

Both of these test statistics have two limitations. First, they test the hypothesis that an individual variance ratio is one; however, the null hypothesis requires $VR(k) = 1$ for all k. Secondly, they are large sample tests and suffer from low power and poor size properties in small samples. In particular, rather than being normally distributed as the theory states, the VR statistics are severely biased and right skewed for large k (relative to the sample size) (Lo and Mackinlay (1989), which make the application of the statistic problematic. Therefore, the finite-sample null distribution of the test statistic is quite asymmetric and non-normal.

The first weakness was addressed by Chow and Denning (1993) who showed that the joint test can be carried out by comparing a set of variance ratio estimates with unity. This involves calculating the test statistic for m different values of k and selecting the one with the maximum absolute value. This is then compared with the appropriate critical value from the studentised maximum modulus distribution. The second limitation has been approached in different ways by Wright (2000) who generated test statistics which have exact distribution under the null hypothesis. Kim (2006) solved the same problem using bootstrapping technics. In the same vein, Chen and Deo (2006) proposed the power transformed test.

Wright's variance ratio tests use the ranks and signs for the return series. Given the series of asset returns r_t, with associated ranks $r(y_t)$, Wright (2000) defined two random variables

$$r_{1t} = \left(r(y_t) - \frac{T+1}{2}\right) \div \sqrt{\frac{(T-1)(T+1)}{12}} \tag{5}$$

which has sample mean and variance of 0 and 1, respectively, and

$$r_{2t} = \phi^{-1}\big(r(y_t)\big) \tag{6}$$

where ϕ^{-1} is the inverse of the standard normal cumulative distribution function and r_{2t} has sample mean and variance of 0 and approximately 1, respectively. For two rank-based variance ratio tests, asset returns, y_t are replaced by these transformations of their ranks in the expression for $VR(k)$, and hence in the test statistic $M_1(k)$ to give

$$R_1(k) = \left(\frac{\frac{1}{Tk}\sum_{t=k}^{T}(r_{1t} + r_{1t-1} + \cdots + r_{1t-k+1})^2}{\frac{1}{T}\sum_{t=k}^{T} r_{1t}^2} - 1\right) \times \left(\frac{2(2k-1)(k-1)}{3kT}\right)^{-\frac{1}{2}} \tag{7}$$

and

$$R_2(k) = \left(\frac{\frac{1}{Tk}\sum_{t=k}^{T}(r_{2t} + r_{2t-1} + \cdots + r_{2t-k+1})^2}{\frac{1}{T}\sum_{t=k}^{T} r_{2t}^2} - 1\right) \times \left(\frac{2(2k-1)(k-1)}{3kT}\right)^{-\frac{1}{2}} \tag{8}$$

Under the null hypothesis that asset returns are iid, and hence the asset price follows a random walk with drift, the exact sampling distribution of $R_1(k)$ and $R_2(k)$ are given in Proposition 1 (Wright, 2000:3) and can easily be simulated to any arbitrary degree of accuracy for an exact test.

Wright (2000) also developed a sign-based variance ratio test under the assumption of martingale difference returns permitting conditional heteroscedasticity. This is based on the iid $s_t \sim iid(0,1)$ where each s_t is equal to 1 with probability $\frac{1}{2}$; and -1 with the same probability.

The sign-based variance ratio is defined using s_t in the place of asset returns in the previous equation and hence to give

$$S_1(k) = \left(\frac{\frac{1}{Tk}\sum_{t=k}^{T}(s_t + s_{t-1} + \cdots + s_{t-k+1})^2}{\frac{1}{T}\sum_{t=k}^{T} s_{2t}^2} - 1 \right) \times \left(\frac{2(2k-1)(k-1)}{3kT} \right)^{-\frac{1}{2}} \tag{9}$$

If the returns are positive $s_t = 1$ otherwise $s_t = -1$.

This test is exact even in the presence of conditional heteroscedasticity and the sampling distribution of the test statistic is given in Proposition 2 (Wright, 2000:3-4).

Following the approach suggested by Chow and Denning (1993), Wright's individual test can be extended to joint test by calculating each test statistic for m different values of k and selecting the one with the maximum absolute value

$$JR_1 = \max\ |R_1(k_i)|$$

The statistic JR_1 also has an exact distribution and finite sample critical values for this joint test are obtained by simulation, Kim (2006) and Belaire-Franch and Contreras (2006). The same procedure is used for the two other joint tests,

$$JR_2 = \max\ |R_2(k_i)|$$

and

$$JS = \max\ |S_1(k_i)|$$

Kim (2006) proposed using the wild bootstrap to improve the small simple properties of joint variance ratio tests. Bootstrapping is a computer intensive resampling method which approximates the sampling distribution of the test statistic, and it is applicable to data with unknown form of conditional and unconditional heteroscedasticty. The wild bootstrap for the Chow and Denning test can be constructed in three stages as below:

1. Form a bootstrap sample of T observations $x_t^* = \eta_t x_t (t = 1, \ldots, T)$ where η_t is a random sequence with zero mean and unit variance
2. Calculate MV^* with the MV statistic obtained from the bootstrap sample generated in stage 1
3. Repeat 1 and 2 sufficiently many, say m, times to form bootstrap distribution of the statistic $\{MV^*(j)\}_{j=1}^{m}$.

The bootstrap distribution $\{MV^*(j)\}_{j=1}^{m}$ is used to approximate the sampling distribution of the MV statistic. The p-value of the test is estimated as the proportion of $\{MV^*(j)\}_{j=1}^{m}$ greater than the MV statistic calculated from the original data. The test that we used in this paper is based on a Chow and Denning (1993) the joint version of the LOMAC test statistic $M_2(k)$ given by equation (4) selecting the maximum absolute value from a set of m test statistics,

$WB = |M_2(k)|$

To tackle the problem of non-normality, biasedness and right skewness of the statistic, Chen and Deo (2006) suggested a simple power transformation of the VR statistic that, when k is not too large, provides a better approximation to the normal distribution in finite samples and is able to solve the well-known right skewness problem. They show that the transformed VR statistic leads to significant gains in power against mean-reverting alternatives. Furthermore, the distribution of the transformed VR statistic is shown, both theoretically and through simulations, to be robust to conditional heteroscedasticity.

First, their proposed VR statistic is based on the periodogram as:

$$VR_p(k) = \frac{1}{(1 - k/T)} \frac{4\pi}{\hat{\sigma}^2} \sum_{i=1}^{(T-1)/2} W_k(\lambda_i) I_{\Delta X}(\lambda_i) \tag{10}$$

where $I_{\Delta X}(\lambda_i) = (2\pi T)^{-1} | \sum_{i=1}^{T} (y_t - y_{t-1} - \hat{\mu}) exp(-i\lambda_i t) |^2$,

and $W_k(\lambda_i) = \sum_{|j| \le k} \left(1 - \frac{|j|}{k}\right) exp(-ij\lambda t) = k^{-1} \left\{ \frac{sin\left(\frac{k\lambda}{2}\right)}{sin\left(\frac{\lambda}{2}\right)} \right\}^2$

To obtain their transformed VR statistic, noted $VR_p^{\beta}(k)$, they applied the following power transformation to the $VR_p(k)$:

$$\beta = 1 - \frac{2}{3} \frac{\left(\sum_{j=1}^{(T-1)/2} W_k(\lambda_i)\right)\left(\sum_{i=1}^{(T-1)/2} W_k^3(\lambda_i)\right)}{\left(\sum_{i=1}^{(T-1)/2} W_k^2(\lambda_i)\right)^2} \tag{11}$$

This power-transformed VR test is an individual test where the null hypothesis is tested for an individual k. To answer the question as to whether or not a time series is mean-reverting requires that the null hypothesis hold true for all values of k. Therefore, it is necessary to conduct a joint test where a multiple comparison of VRs is done for over a set of different time horizons. However, conducting separate individual tests for a number of k values may be misleading because it leads to over-rejection of the null hypothesis of a joint test above the nominal size (Chow and Denning, 1993). Thus Chen and Deo (2006) proposed a joint VR test based on their individual power transformed VR statistic. They suggest the following Wald statistic:

$$QB(k) = \left(V_{p,\beta}(k) - \mu_\beta\right)' \Sigma_\beta^{-1} \left(V_{p,\beta}(k) - \mu_\beta\right)$$

Where $V_{p,\beta}$ is a column vector sequence of VR statistics $V_{p,\beta}(k) = \left[VR_p^{\beta}(2), \dots, VR_p^{\beta}(k)\right]$ with $VR_p^{\beta}(k)$ the power transformed VR as in (11), μ_β and $\Sigma_\beta(k)$ are a measure of the expectation and covariance matrix of $V_{p,\beta}$, respectively. The joint VR $QB(k)$statistic follows a χ^2 distribution with k degrees of freedom.

3. Empirical Results and Discussion

3.1. Data and Description Statistics

The data examined consist of daily and weekly nominal exchange rates for the Algerian dinar, Egyptian pound, Ghanaian cedi, Kenyan shilling, Malawian kwacha, Mauritian rupee, Moroccan dirham, Mozambican metical, Nigerian naira, South African rand, Tanzanian shilling, Tunisian dinar and Zambian kwacha, all relative to US dollar, which includes the important dollar-based exchange rates that are classified as independent floating by international Monetary Fund.The data span January 3, 2000 to February 28, 2017. Weekly observations, consisting of Wednesday closing rates were generated from daily quotes or on the following day if the markets are closed on Wednesday. The nominal exchange rate data were compiled by the International Monetary Fund and were obtained from Bloomberg. We use both frequencies to tacle the problem issues such as bias with daily data (e.g., non-trading, nonsycrhoneous trading, bid ask spread, ecc...) and assumptions about weekly data allow to alternate day price in the case of non-trading on the day of the week is observed.The nominal log returns are derived from the nominal exchange rate i.e $x_t = \log(P_t/P_{t-1})$ where P_t is the value of the nominal exchange rate at time t and log is the natural logarithm.

Figure 1 presents the time plots of daily returns for all markets. The horizontal line in each graph indicate $(Q_1 - 3IQR, Q_3 - 3IQR)$, where Q_1 is the first quartile, Q_3 is the third quartile, and IQR is the interquartile range $(Q_3 - Q_1)$. This is a popular criterious to detect extreme values or outliers based on the Box plot as noted by De Veaux *et al.* (2005). We find extreme outliers in the Egyptian, Ghanean, Nigerian and Malawian currencies. This can be related to political unrest or imposition of capital control which can cause inefficiencies in currency market, see Kim and Shamsuddin (2008). In particular outliers in Egyptian exchange rate markets is due to political events (we provide partially the result for reasons of space the remaining part of the Figure 1 is available under request).

Descriptive statistics for daily and weekly returns are presented in Table 1 and 2, respectively. For daily returns (Table 1). Malawi kwacha exhibits the best perfomance although it is also one of the most volatile currency returns, as the standard deviation shows. Currency return for Morocco exhibits the lowest standard deviation 0.000%, while Mozambique shows the highest dispersion from the mean. The Jarque-Bera statistic is significant at 1 % level for all series, suggesting that foreign exchange rate returns are highly non-normal. The excess kurtosis and skewness indicate that the empirical distributions of foreign exchange rates have fat tail and skewed. The Ljung-Box LB statistic for testing serial correlation shows that all the series are significantly correlated except for South African rand and Kenyan shilling. There is also a widespread evidence of autoregressive conditional heteroscedasticity in daily data. Of the 13 daily series examined, ARCH effet were absent only for Nigeria and Malawi. Accordingly, statistical inference for randomness using the VR tests should be based on the heterescedasticity-adjusted statistic, except for Nigeria and Malawi.

Results for weekly data are displayed in Table 2, all the returns show evidence of significant excess skewness and excess kurtosis and are non-normal as one can infer by the Jarque-Bera test. All the exchange rates are significantly correlated, except for South Africa, Mauritius, Tunisia and Zambia. According to the ARCH test, only the Egypt, Nigeria and Malawi do not exhibit conditional heteroscedasticity. Thus, these three currencies do no need to employ the heteroscedasticity-adjusted statistic.

3.2. Testing the Efficient Market Hypothesis

Tables 3-6 display the results of the individual and multiple VR tests for daily and weekly exchange markets. The holdings periods ($k's$) which represent the multiples of each sampling frequency are calculated for each dataset for the cases $k = 2, 4, 8$ and 16. For individual sample, standard VR, the $M_1(k)$ and the heteroscedasticity-consistent variance-ratio tests are performed by calculating the $M_2(k)$ at the same holding period. The result for these calculations for daily data are presented in Table 3. The variance-ratios are reported in the main rows of the table while the M_1 and M_2- statistics are respectively, given in parentheses and square brackets below each of the main row entries. The test statistic is displayed for the Belaire-Franch and Contreras JR_1, JR_2, JS tests, for the Chen and Deo (2006) $QB(k)$ test, while we provide p-values for the Kim wild bootstrap WB test.

The variance-ratio estimates in Table 3 are less than one for most k and the ratios often decrease with increasing k. Under the maintain hypothesis of homoscedascity, the RWH is rejected for all the currencies tested.

For the Moroccan dirham for instance, the M_1-statistics for $k = 2, 4, 8$ and 16 are $-24.11, -23.46, -17.97, -13.39$ respectively. All four M_1-statistics indicate that the variance ratios are significantly different from the unity at one per cent level. The RWH is therefore soundly rejected for the Moroccan dirham for all four intervals examined. By similar analysis, the remaining M_1-statistics in Table 3 present evidence strongly rejecting the RWH hypothesis in the remaining twelve currencies.

The rejection of the RWH under the hypothesis of homoscedasticity could be due to the presence of heteroscedasticiy and/or serial correlation. We applied the heteroscedasticity-consistent variance-ratio test. The RWH is robust to heteroscedascity in nine of thirteen currencies and so, for these nine currencies, the evidence suggests that the RWH is rejected because of autocorrelation of daily increments in the exchange rate series. In the remaining four, (Egyptian pound, Kenyan shilling, South-African rand and Zambian kwacha), the heteroscedascity-adjusted tests fail to reject the RWH. This suggests that the rejection for these four currencies maybe due to the presence of heteroscedasticity in the exchange rate series (or extreme values).

Rejection of the iid RWH for Morocco is confirmed by the multiple VR tests (Table 5), which also reject the null hypothesis for the remaining exchange rate series. Note that JS does not reject the null hypothesis for the South-African rand, but Belaire-Franch and Contreras (2004) show that the rank-based tests are more powerful than the sign-based tests. In principle, this rejection could be the result of either the autocorrelation in exchange rate return or various forms of dependence in higher moments. However, the joint sign test does not reject the hypothesis that the South-African rand is martingale difference sequence. When applying Chen and Deo and Kim wild bootstrap to our daily sample, we cannot reject RWH for Egyptian pound, Kenyan shilling, South-African rand and Zambian kwacha. The joint sign test rejects the null hypothesis that the return are mds satisfying Assumption $A1$ and $A2$ of Wright (2000) and a null drift. The wild bootstrap joint variance ratio test nor the power transformed Chen and Deo do not reject the hypothesis that the daily exchange rate returns are an mds satisfying the Assumption H* of LOMAC. This is sufficient but not necessary, for the inference that daily exchange rate returns for Egypt, Kenya, South-Africa and Zambia are mds. We note higher value in the QB statistic for Algeria, Mauritius and Morocco. This is due to outliers value as we can see from Figure 1, in general, we note that JS is free from the effect of outliers. However, it appears that outliers occurred in the Egyptian pound were not influential to the outcomes of the test.

For weekly data, the results for individual VR tests are presented in Table 4. Under the maintain hypothesis of homoscedasticity, the RWH cannot be rejected for six currencies (Ghanaian cedi, Kenyan shilling, Mauritian rupee, South-African rand, Tunisian dinar and Zambian kwacha) but we find evidence of inefficiency in the remaining exchange rate currencies. To explore these mixed results further we appeal to heteroscedasticity -consistent random walk tests. The results, also reported in Table 4, show that the RWH can be rejected for four exchange rate series namely, Algerian dinar, Malawian kwacha, Moroccan dirham and Nigerian naira.

For all weekly exchange rate returns, we can infer from the results for multivariate VR tests that the iid random walk is rejected. The joint sign test rejects the martingale hypothesis for all currencies markets except for Algerian, Tanzanian and South-African currencies since the computed statistic is lower than the critical values, however, for Egyptian, Ghanaian, Kenyan, Mauritian, Tanzanian, Tunisian, South African and Zambian currencies, neither the wild bootstrap test nor the Chen and Deo variance ratio tests reject the martingale hypothesis.

The overall result from individual variance ratio tests suggests a rejection of the RWH for all the daily exchange rates in our sample. This rejection maybe due to the presence of serial correlation in the exchange rate series as indicated by most variance ratio estimates of less than unity, or maybe due to heteroscedasciticy since heteroskedasticity-adjusted tests reject the RWH less often than homoscedasticity consistent tests. Test results for weekly data are mixed. The RWH is rejected for ten currencies under homoscedasticity, while the heteroskedasticity-adjusted tests fail to reject RWH for seven currencies. This suggests that for the rejection of the RWH for these weekly data are not robust to heteroscedasticity.

In summary, for multiple VR tests, not one of African exchange rate currencies considered here follows an iid random walk. In nine currencies of our sample the martingale hypothesis is also rejected. In four exchange rate series, Egyptian pound, Kenya shilling, South-African rand and Zambian kwacha daily returns are mds; these results are supported by the evidence from tests on weekly exchange rate returns series. Among the nine (09) daily exchange rate currency returns which are non mds, the martingale hypothesis is rejected at weekly frequency only for the Algerian dinar, the Malawian, the Moroccan dirham and the Nigerian naira. It is likely that the results from daily data are the consequence of more powerful testing because they are based on a large sample size Kim and Shamsuddin (2008). Also day-to-day autocorrelation can be detected with higher frequency data; this is difficult when weekly series are used.

Our results are different from the one of Anoruo and Braha (2015) who analyzed the RWH of currencies returns of 15 African countries and find evidence against random walk behavior for currency returns of all sample countries, they also differ from the findings of Mbululu et al. (2013) who rejected the RWH for Zambian kwacha. The two studies used the seminal variance ratio tests and Wright (2000) test. Therefore, our study suggests that using the Kim (2006) and Chen and Deo (2006) tests are more powerful since these are robust to outliers and structural changes. The problem in reconciling these results is the different sample periods, frequency and methodologies employed by different researchers

The rejection of the RWH by the variance ratio tests for African currencies suggests important economic implications. First as stated by Lo-Mackinlay (1989) and adopted later in Liu and He (1991) or Ajayi and Karemera (1993) the use of variance ratio provides a convenient way to differentiate between the overshooting or undershooting phenomena in exchange rates. In this study, most estimates of the variance ratios are less than unity, suggesting the presence of negative serial correlation in the series. The presence of negative serial correlation in an exchange rate overshooting has been linked to the phenomena of exchange rate overshooting and official intervention in the market. Second, evidence against the RWH in exchange rates lends some support to classical monetary models of exchange rates which retain the purchasing power parity (PPP) as a long-run equilibrium condition. Third, the rejection of RWH presents opportunities for higher–than–average market return on the exchange rate through technical and fundamental analysis if the transaction cost are trivial. Therefore, such a rejection have interesting implications for exchange rate forecasting, currency futures and options pricing, and investors' international portfolio choices. The African currencies, like other commodities driven currencies rarely follows the random walk process. The exchange rate is, to a large extent determined by foreign-currency flows and as such one expects the exchange rates to follow a non-random walk pattern. As noted by the (World Bank 2005), the African currency trading market is dominated by large multinational banks. These banks keep foreign–currency accounts for multinationals and development organizations the major foreign exchange participants. Most foreign-currency flows therefore end up in just a few banks. The results is that trading is concentrated in these select few banks, which are able to influence market rates mainly due to the relationship, or as result of loan agreements. These agreements result from the bank's extension of loans to multinationals in which they agree to transact foreign exchange between themselves. In most cases, the agreements are entered into at head-office level. This simply means that banks tie their loans facilities to foreign exchange business, a huge source of non-funded income resulting in the crowding out of the banks. This promotes inefficiency in the market.

4. Conclusion

This papers tests iid random and martingale hypothesis for 13 exchange rate currencies (Algerian dinar, Egyptian pound, Ghanean cedi, Kenyan shilling, Malawian Kwacha, Mauritian rupee, Moroccan dirham, Mozambican metical, Nigerian naira, South African rand, Tanzanian shilling, Tunisian dinar and Zambian kwacha relative to US dollar). This exercise is important because the martingale property has strong implication for currency markets in the weak-form. In this study, we use a battery of recent joint variance ratio tests based on the ranks and signs, wild bootstrap and power transformed tests, in addition to the conventional Chow and Denning test. Not one of the markets follows an iid random walk. For the Algerian dinar, Ghanaian cedi, Malawian kwacha, Mauritian rupee, Moroccan dirham, Mozambican metical, Nigerian naira, Tanzanian Shilling and Tunisian dinar hypothesis of martingale difference sequence is also rejected. In four currencies market, those of Egypt, Kenya, South-Africa and Zambia, daily returns form a martingale difference sequence; these results are supported by evidence from tests on weekly returns. For Algeria, Malawi, Morocco and Nigeria both random walk and martingale hypotheses is rejected for weekly returns. The different results from tests of the martingale hypothesis for the currency markets probably occur because day-to-day negative serial correlation can be detected with higher frequency data; this is probably less present when weekly series are used. The presence of negative serial correlation in exchange rates had been linked with to exchange rate overshooting, and official intervention in the foreign exchange market. In addition evidence against random walk in exchange rates lends some support to classical monetary models of exchange rates which retains the PPP as a long term equilibrium. The rejection of RWH presents opportunities for higher–than–average market return on the exchange rate through technical and fundamental analysis if the transaction costs are trivial. Therefore, such a rejection has interesting implications for exchange rate forecasting, currency futures and options pricing, and investors' international portfolio choices.

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Table 1: Descriptive statistics for daily log exchange rate returns

	Mean	SD	Skewness	Kurtosis	JB	LB(12)	ARCH
ALGERIA	1.08	1.02	-0.083	9.95	8961*	612.08*	702.67*
EGYPT	3.45	0.86	34.44	1680.74	520330000*	97.82*	25,48**
GHANA	5.92	1.17	1.20	33.90	175560*	505.98*	586.53*
KENYA	0.78	0.50	0.36	21.68	64822*	0.94	813.43*
MALAWI	6.22	1.04	15.32	597.39	65197000*	234.42*	0.90
MAURITIUS	0.75	0.74	0.50	16.82	35563*	720.80*	787.95*
MOROCCO	0.00	0.00	-0.36	44.61	322860*	582.64*	868.93*
MOZAMBICO	3.80	1.44	0.93	39.60	245750*	755.13*	986.44*
NIGERIA	2.61	1.15	6.61	215.59	8322100*	288.36*	7.53
SOUTH-AFRICA	1.69	1.10	0.95	14.29	24459*	2.07	476.70*
TANZANIA	2.34	0.68	-0.734	47.66	365770*	144.27*	870.46*
TUNISIA	1.36	0.49	-0.02	4.88	653.58*	39.12*	228.29*
ZAMBIA	2.76	1.22	-1.06	23.59	78804*	6.05**	417.81*

The mean values are multiplied by 10^4, The standard deviation values are multiplied by 10^2 . * and ** mean respectively significant at 1% and 5% level

Table 2: Descriptive statistics for weekly log exchange rate returns

	Mean	SD	Skewness	Kurtosis	JB	LB(12)	ARCH
ALGERIA	5.4	1.23	0.23	6.61	494.99*	17.152*	83.246*
EGYPT	17.1	2.50	22.05	486.3	12732000*	14.7*	1.30
GHANA	27.98	1.83	0.28	23.93	16324*	0.96	137.82*
KENYA	3.95	1.08	0.02	17.03	7340.10*	23.34*	207.63*
MALAWI	30.79	1.89	11.3	235.18	2027000*	18.42*	0.09
MAURITIUS	3.90	1.05	0.62	9.01	1405.2*	3.46	166.58*
MOROCCO	0.00	0.00	0.08	25.75	19283*	93.43*	190.66*
MOZAMBICO	18.71	2.06	1.57	27.37*	22491*	23.438*	47.41
NIGERIA	12.9	1.95	6.73	127.82	587080*	25.2*	1.56
SOUTH-AFRICA	8.50	2.42	0.53	8.64	1228.3*	0.22	190.89*
TANZANIA	11.55	1.22	-0.97	30.08	27436*	40.28*	210.11*
TUNISIA	7.00	1.02	-0.27	5.58	258.27*	0.67	56.2*
ZAMBIA	14.00	2.74	-1.58	19.45	10458*	2.45	45.84*

The mean values are multiplied by 10^4, The standard deviation values are multiplied by 10^2 . * and ** mean respectively significant at 1% and 5% level

Table 3: Individual variance ratio test results for daily data

		K		
	2	4	8	16
ALGERIA	0.6293 (-24.7223)* [-12.469]*	0.3898 (-21.7542)* [-11.5967]*	0.2611 (-16.6606)* [-9.5449]*	0.2228 (-11.7764)* [-7.1293]*
EGYPT	1.1491 (9.9216)* [1.0662]	1.3685 (13.1094)* [1.5679]	1.4108 (9.2423)* [1.3359]	1.4753 (7.1866)* [1.2651]
GHANA	0.6395 (-23.8713)* [-7.1799]*	0.4758 (-18,5562)* [-6.1976]*	0.4382 (-12.5764)* [-4.5551*	0.4529 (-8.2301)* [-3.0814]*
KENYA	0.9858 (-0.9464) [-0.3336]	0.8967 (-3.6823)* [-1.3179]	0.8757 (-2.8023)* [-1.0658]	0.8985 (-1.5387) [-0.6463]
MALAWI	0.7705 (-15.2552)* [-6.3466]*	0.6966 (-10.7793)* [-4.6196]*	0.7379 (-5.8896)* [-2.7018]*	0.8841 (-1.7495)* [0.8871]
MAURITIUS	0.5975 (-26.8309)*	0.4201 (-20.6632)*	0.3778 (-14.0211)*	0.4097 (-8.9402)*

	[-10.0621]*	[-8.7148]*	[-6.6973]*	[-4.7220]*
MOROCCO	0.6394 (-24.1199)* [-6.1266]*	0.3440 (-23.4554)* [-6.2403]*	0.2052 (-17.9739)* [-5.1060]*	0.1192 (-13.3862)* [-4.0776]*
MOZAMBIQUE	0.5856 (-27.4632) [-6.6222]	0.3977 (-21.3337) [-5.7264]	0.3144 (-15.3593) [-4.6191]	0.3105 (-10.3807) [-3.6301]
NIGERIA	0.7445 (-16.9546)* [-5.9234]*	0.5822 (-14.8161)* [-5.8113]*	0.4793 (-11.6786)* [-5.2396]*	0.4415 (-8.4184)* [-4.2769]*
SOUTH-AFRICA	0.9788 (-1.4152) [-0.8381]	0.9251 (-2.6780)** [-1.6715]	0.8763 (-2.7977)** [-1.7471]	0.8759 (-1.8859) [-1.1724]
TANZANIA	0.8190 (-11.9980)* [-2.9911]*	0.6945 (-10.8278)* [-2.9667]*	0.5496 (-10.0947)* [-3.0890]*	0.4804 (-7.8264)* [-2.6421]*
TUNISIA	0.9058 (-6.2866)* [-5.4005]*	0.8757 (-4.4353)* [-3.7034]*	0.8970 (-2.3241)** [-1.9439]	0.9499 (-0.7602) [-0.6506]
ZAMBIA	0.9633 (-2.4376)* [-1.0051]	0.9656 (-1.2231) [-0.5105]	0.9768 (-0.5207) [-0.2384]	0.9675 (-0.4908) [-0.2529]

Table 4: Individual variance ratio test results for weekly data

		k		
	2	4	8	16
ALGERIA	0.8626 (-4.1074)* [-2.8358]*	0.7184 (-4.5003)* [-3.2348]*	0.7078 (-2.9535)* [-2.2060]**	0.7303 (-1.8321) [-1.3872]
EGYPT	0.8719 (-3.8295)* [-0.9552]	0.9500 (-0.7981) [-0.2029]	1.0542 (0.5478) [0.1696]	1.0454 (0.3080) [0.1229]
GHANA	0.9627 (-1.1167) [-0.3842]	0.9331 (-1.0693) [-0.3890]	1.0086 (0.0868) [0.0354]	1.3247 (2.2056)** [1.0254]
KENYA	0.9453 (-1.6342) [-0.8370]	0.9883 (-0.1877) [-0.0939]	1.1187 (1.2001) [0.5965]	1.1387 (0.9421) [0.486]
MALAWI	1.1461 (4.3685)* [4.4433]*	1.4289 (6.8553)* [6.9737]*	1.8089 (8.1762)* [7.9358]*	2.0374 (7.0466)* [7.5159]*
MAURITIUS	0.9397 (-1.8037) [-1.0862]	1.0570 (0.9107) [0.5484]	1.1623 (1.6408) [0.9932]	1.2930 (1.9901)** [1.2106]
MOROCCO	0.6781 (-9.6237)* [-4.7008]*	0.3521 (-10.3549)* [-4.1768]*	0.1899 (-8.1881)* [-3.3319]*	0.1136 (-6.0209)* [-2.6520]*
MOZAMBIQUE	0.8398 (-4.7889)* [-1.8482]	0.8431 (-2.5072)* [-1.0795]	0.8495 (-1.5215) [-0.7570]	1.0135 (0.0919) [0.0521]
NIGERIA	0.8338 (-4.9695)* [-2.5131]*	0.7696 (-3.6821)* [-2.1719]**	0.8624 (-1.3906) [-0.8766]	0.8956 (-0.7093) [-0.4780]
SOUTH-AFRICA	0.9863 (-0.4084) [-0.2459]	0.9143 (-1.3697) [-0.7737]	0.9279 (-0.7289) [-0.4370]	0.9494 (-0.3439) [-0.2327]
TANZANIA	0.7893	0.7524	0.7537	0.7656

		k		
	2	4	8	16
	(-6.2968)* [-1.6583]	(-3.9557)* [-1.1964]	(-2.4880)* [-0.9221]	(-1.5916) [-0.7250]
TUNISIA	1.0295 (0.8815) [0.7960]	1.0963 (1.5396) [1.4019]	1.1644 (1.6613) [1.4794]	1.2315 (1.5727) [1.3746]
ZAMBIA	0.9502 (-1.4883) [-0.8810]	0.9493 (-0.8107) [-0.4629]	1.0286 (0.2887) [0.1744]	1.0855 (0.5805) [0.3751]

Table 5: Multiple variance ratio test for daily data

	JR1	**JR2**	**JS1**	**QB**	**WB**
ALGERIA	17.02*	20.23*	8.85*	276.58*	0.00*
EGYPT	14.08*	14.16*	14.05*	3.89	0.170
GHANA	18.22*	20.28*	10.04*	64.36*	0.00*
KENYA	2.47*	1.96	4.89*	5.09	0.338
MALAWI	10.57*	14.51*	21.75*	62.57*	0.00*
MAURITIUS	17.78*	21.05*	12.58*	159.24*	0.00*
MOROCCO	24.385*	24.82*	85.09*	88.90*	0.00*
MOZ	18.76*	21.71*	27.48*	69.49*	0.00*
NIGERIA	14.006*	15.81*	8.000*	52.39*	0.00*
SOUTH-AFRICA	2.37	2.62*	1.69	4.97	0.15
TANZANIA	8.47*	9.70*	7.45*	16.20*	0.01*
TUNISIA	6.66*	6.59*	5.35*	34.11*	0.00*
ZAMBIA	2.24	1.952	7.39*	1.51	0.56

- and ** critical values at 1% and 5% arerespectively

The 0.05 critical value for JR1;JR2 and JS 2.340;2.361 and 2.341 . P-value for WB

Table 6: Multiple variance ratio test for weekly data

	JR1	**JR2**	**JS1**	**QB**	**WB**
ALGERIA	2.88*	3.83*	1.53	14.92*	0.00*
EGYTP	9.84*	9.45*	6.18*	7.39	0.75
GHANA	9.76*	7.75*	7.18*	5.82	0.64
KENYA	3.37*	3.00*	3.33*	3.012	0.69
MALAWI	11.91*	13.47*	9.85*	40.06*	0.00*
MAURITIUS	3.82*	3.09*	6.06*	7.34	0.49
MOROCCO	11.49*	11.32*	23.90*	42.79*	0.00*
MOZAMBIQUE	6.94*	5.33*	7.93*	9.40	0.10
NIGERIA	3.02*	3.95*	3.17*	10.58*	0.012*
SOUTH-AFRICA	0.38	1.13	1.00	1.86	0.75
TANZANIA	1.28	1.70	1.92	4.05	0.15
TUNISIA	3.09*	2.24*	4.44*	2.40	0.34
ZAMBIA	2.29*	1.89	3.85*	2.30	0.64

* and **The critical values at 1% and 5% are respectively 3.022; 2.49
The 0.05 critical value for JR1;JR2 and JS 2.340;2.361 and 2.341 . P-value for WB

Figure 1: Time plot of log exchange returns