Long Memory or Structural Breaks: Some Evidence for African Stock Markets

Geoffrey Ngene [a*], Kenneth A. Tah [b, c], Ali F. Darrat [b]

[a] *Stetson School of Business and Economics, Mercer University, Macon, GA, 31207*
[b] *College of Business, Louisiana Tech University, Ruston, LA , 71272*
[c] *College of Business, Grambling State University, Grambling, LA, 71245*

Abstract

We explore whether weekly stock returns and variance of several African stock markets exhibit long memory behavior. We assess return and variance dependency in the presence and absence of structural breaks using the semi-parametric Robinson test and the ARFIMA-FIEGARCH parametric methods. We find evidence of significant structural shifts in returns and variance in most markets. When structural breaks are ignored, the results indicate the existence of long memory components in stock returns and variance in the majority of the African markets. However, once structural breaks are introduced in the testing models, the long memory evidence significantly dissipates and the results support instead short memory behavior across markets. These findings suggest that long memory inferences are likely episodic and could be disguising short memory behavior with regime shifts. Consequently, caution is warranted when interpreting long memory inferences in the presence of structural breaks.

Keywords: long and short memory, market efficiency, stock returns, African markets

JEL Classifications: G12, G14

* *Corresponding author*: Email: ngene_gm@mercer.edu; phone: (478) 301-2719.

Long Memory or Structural Breaks:
Some Evidence for African Stock Markets

1. Introduction

In its semi-strong form, the stock market efficiency (SME) hypothesis contends that stock prices fully incorporate any new information as soon as they become publicly available. Therefore, there should be no exploitable (low-frequency) components in stock prices for predicting future prices and earning abnormal returns without additional risk. Consequently, the presence of such low-frequency or long memory components contradicts market efficiency. Long memory (also called long-range dependency or persistency) occurs when the statistical dependence in stock prices returns decays slowly over time.

The existence of long memory in asset return suggest that current returns are severely dependent on distant past realized returns. This not only creates opportunities for arbitrage profits but it also makes it possible for future returns to be predicted from past returns, a fact that violates the efficient market hypothesis and martingale processes which are assumed in most financial asset pricing models. Lo (1991) also suggests that long memory in asset returns makes portfolio allocation and consumption (saving) decisions more sensitive to investment horizons. Therefore, detection of long memory should be useful to regulators and policymakers in their attempt to mitigate market inefficiency.

In relation to variance of returns, the finding of long memory component in volatility should affect the pricing of long-term options and optimal portfolio allocations which are susceptible to investment horizons. Optimal hedging strategies must take into account the short- and long-range dependences of volatility. In addition, long memory in volatility has profound implications for market predictability and risk premium. According to French *et al*. (1987), risk premium and volatility of returns are closely related.

However, inferences on long memory models may prove spurious in the presence of structural breaks (Cheung, 1993a and Diebold and Inoue, 2001). More recently, Cappelli and Angela (2006) argue that stationary short memory processes with occasional structural breaks may slow down the rate of decay in the autocorrelation function and other fractionally integrated processes. Therefore, structural breaks could cause long memory and the latter may also spuriously detect structural breaks. Baillie et al. (1996) examine the price behavior during hyperinflation using the fractionally integrated ARFIMA-GARCH process but without considering the possibility of structural breaks. They report that hyperinflation in three countries is mean-reverting with a non-stationary process. However, in their re-examination of the same price data, Caporale and Gil-Alana (2003) conclude that the degree of inflation persistence is markedly lower once breaks are taken into account.

The evidence for long memory in US stock returns is unclear. While Lo (1991) and Ambrose *et al*. (1993) deny the presence of long memory in stock returns; DiSario *et al*. (2008) support its existence. Allowing for short dependence, Hays, Rajagopal and Schrieber (2010) find long memory in stock returns but only in the recent turbulent period. For markets in Europe, Barkoulas *et al.* (2000) and Sibbertsen (2004) report some evidence of long memory in Greek and Germany stock returns, respectively; while Cheah and Lee (2008) fail to discover any evidence of long memory in the UK market.

As to African stock markets, Anoruo and Gil-Alana (2011) examine long memory in several African countries using the fractional integration method. While rejecting the mean reversion behavior in all sampled markets, their results are broadly consistent with long memory returns in most of them. Assaf (2007) and Alagidede (2011) explore the case of developing economies in Africa and the Middle East and report evidence of long memory in the majority of these equity markets. In their examination of time-varying volatility in African stock markets, McMillan and Thupayagale (2011) suggest that estimates of long memory in volatility are sensitive to structural breaks.

In this paper, we study whether weekly stock returns across eight African stock markets exhibit long-term memory behavior in the presence of structural breaks. Our paper differs from previous studies on African stock markets in at least four respects. First, most African stock markets, with the exception of South Africa's Johannesburg Stock Exchange, are illiquid and thinly traded due to non-synchronous trading. According to Miller *et al.* (1994), this can cause serial correlation of returns. Unlike prior studies, we adjust the returns for thin trading to ensure that any evidence of long memory (or the lack thereof) is not due to thin trading-induced serial correlation of returns. Second, we test for the effects of inflation and exchange rates on long memory behavior. This is crucial since long memory evidence in stock returns (denominated in U.S dollar and local currency) may merely reflect long memory in exchange rates and inflation. Third, we account for structural breaks in mean returns and in volatility of stock returns since volatility impacts risk premium associated with any investment. And fourth, we use both the semi-parametric method of Robinson (1995) and Sowell (1992) parametric method to check the robustness of our empirical evidence.

The rest of the paper is organized as follows. Section 2 discusses the data and their characteristics. Section 3 outlines the research design. Section 4 presents the empirical results. Section 5 concludes.

2. Data and their characteristics

We focus on the seven major stock markets in Africa; namely, Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa and Tunisia.[1] For comparison with a mature market, our sample includes the US Wilshire 5000 index which comprises 6,700 stocks of small, mid and large-cap US firms. We compile Wednesday-to-Wednesday closing weekly stock price indices over the period June 5, 2002 to February 26, 2014, yielding a sample of 613 weekly observations. The indices are denominated in US dollar and local currencies. We use both currencies to explore the potential effects of exchange rates (between US dollar and local currency) on long memory. We use Wednesday-to-Wednesday closing prices to avoid problems caused by day-of-the week effects (Lo, 1991). The stocks returns are computed as natural log differences of each index. The stock indices data come from Morgan Stanley capital International (MSCI) website. We also collect monthly consumer price indices (CPI) for each country from IMF's international Financial Statistics (IFS)[2]. We take the local currency-denominated returns and deflated them by the country-specific inflation rates to generate local currency-denominated real returns. Thus, we have three weekly stock return series; namely, US dollar-denominated returns, local currency-denominated nominal returns and local currency-denominated real returns.

One of the major problems that plagues small stock markets of frontier and emerging countries is non-synchronous trading and non-trading. According to Merton *et al*. (1994), non-synchronous trading arises where stocks trade every successive trading interval but generally fail to trade at the close of the interval. Non-trading arises when the stocks fail to trade at every consecutive interval. If the trading intervals contract, then non-synchronous trading eventually

[1] Data availability and consistency dictated the selection of these particular African countries.

[2] Several reasons piqued our use of data from MSCI and from IFS. In particular, the MSCI stock indices and CPI are constructed using a consistent methodology across all sample countries which makes it easier to compare different countries. These stock indices also represent at least 60% of market capitalization, comprising the most liquid equity securities in local markets.

becomes non-trading. Both non-synchronous and non-trading are due to thin trading primarily caused by inadequate buy or sell orders. Thin trading induces serial dependence of stock returns since prices recorded at the end of a given period or interval represent the outcome of prior period transactions. To avoid contaminating our results by thin trading and illiquidity, our three stock returns series of each country are de-thinned using the following AR (1) manipulation of Miller *et al*. (1994):

$$R_{i,j,t} = \beta_{i,j,0} + \beta_{i,j,1} R_{i,j,t-1} + e_{i,j,t} \tag{1}$$

$$R_{i,j,t}^{adj} = \frac{e_{i,j,t}}{\left(1-\beta_{i,j,1}\right)} \tag{2}$$

Where $R_{i,j,t}$ is the return of series *i* (for *i=1, 2, 3*) of country *j (*for *j=1, 2, 3……7)* in week *t* (for *t=1, 2….T*). $R_{i,j,t-1}$ is the lag of dependent variable while $e_{i,j,t}$ is the Gaussian residuals. $R_{i,j,t}^{adj}$ is the de-thinned returns of each series. De-thinned returns are used in all our subsequent analysis.

3. Econometric methodology

We use the autoregressive fractionally integrated moving average (ARFIMA) model of Granger and Joyeux (1980) and commonly dubbed as ARFIMA$\left(p, \phi_1, q\right)$. In this model, *p* and *q* are the autoregressive (*AR)* and moving average (*MA)* lag orders capturing short memory, while ϕ_1 denotes the long memory or non-integer fractional differentiation. The parameter ϕ_1 falls between zero and one hence $\phi_1 \in (0,1)$. The description of ARFIMA process is as follows. Consider a stochastic process, y_t with mean μ. An ARFIMA $\left(p, \phi_1, q\right)$ process is:

$$\psi(L)(1-L)^{\phi_1}\left(y_t - \mu\right) = \varphi(L)\varepsilon_t \tag{3}$$

Where $\varepsilon_t \sim i.i.d.\left(0, \sigma_\varepsilon^2\right)$

In equation 3, L is the lag operator while ψ and φ denotes the *AR* and *MA* lag polynomials. ϕ_1 is the fractional difference or long memory parameter. If $\phi_1 = 0$, the ARFIMA model collapses to the traditional ARMA (*p, q*) model.

The estimation of ϕ_1 parameter in ARFIMA model is sensitive to the selection of *AR* and *MA* terms. Therefore, we first run an ARMA model to select the optimal *AR* and *MA* terms using Swartz Bayesian information (BIC) criteria. We then identify the final *AR* and *MA* terms noting the need for parsimony of the model and convergence in estimation of parameters. We display the corresponding *AR* and *MA* terms in the second row of Table 5 and 6.

When estimating the ARFIMA model, we use the efficient Sowell's (1992) exact maximum likelihood estimation (EMLE). This method permits the concurrent estimations of AR and MA coefficients (*p* and *q)* as well as the long-term memory parameter ϕ_1, all of which are necessary to identify the ARFIMA (*p,* ϕ_1 *q*) process. The EMLE procedure assumes that the residuals from ARFIMA equation 3 are normally distributed. Under this assumption, the log-likelihood function for a sample with *N* observations is:

$$L(\varpi; y_N) = -\frac{N}{2}\log 2\pi - \frac{1}{2}\log\left|\sum\nolimits_N\right| - \frac{1}{2}\left(y_N' \sum\nolimits_N^{-1} y_N\right) \tag{4}$$

The MLE is derived by maximizing expression (3) with respect to $\varpi = (\psi, \varphi, \phi_1)$. The parameter ϖ is both consistent and asymptotically normal. The estimation of $\sum_N$ (the covariance function of the model parameters) is computationally difficult since the likelihood function requires inverting the $\sum_N$ matrix of order *N x N.*

Bollerslev and Mikkelsen (1996) extend the Fractional integrated GARCH (FIGARCH) of Baillie *et al.* (1996) to accommodate the leverage effects (asymmetric effects of positive and negative shocks). They developed the FIEGARCH model which imitates the ARFIMA long memory effect in volatility, thus permitting a hyperbolic decay of the *d* coefficient in Exponential GARCH model of Nelson (1991). The FIEGARCH (*p*, *d*, *q*) model is given as

$$\beta(L)(1-L)^d \ln(\sigma_t^2) = \omega + \sum_{j=1}^{q}\left(\gamma_j z_{t-j} + \lambda_j\left(|z_{t-1}| - E|z_{t-1}|\right)\right) \qquad (5)$$

In equation 5, $z_t = \varepsilon_t \sigma_t^{-1}$ is the standardized and *i.i.d* white noise residuals while $\gamma_j z_t + \lambda_j\left[|z_t| - E|z_t|\right]$ is the news impact function. The parameter γ captures asymmetric effects where if $\gamma < 0$, then conditional volatility will proportionately be magnified more by a negative past shock than by a positive shock of equal magnitude. The term $\lambda\left[|z_t| - E|z_t|\right]$ captures the size of the shock effects. L is the backshift or lag operator and all the roots of autoregressive polynomial (*p* or GARCH term represented by parameter β) and moving average (*q* or MA or ARCH term) polynomial in *L* lie outside the unit circle. *AR* and *MA* do not have a common root. When *d=0*, the FIEGARCH (*p*, *d*, *q*) process reduces to EGARCH of Nelson (1991), and when *d=1*, the process becomes integrated EGARCH (IEGARCH). Bollerslev and Mikkelson (1996) report supportive evidence for the efficiency of quasi-maximum-likelihood estimates (QMLE) in obtaining an asymptotic robust covariance matrix in the estimation of FIEGARCH parameters. We use Schwarz Bayesian information (BIC) as our model selection criterion. Bollerslev and Mikkelsen (1996) demonstrate that the FIEGARCH model is stationary for all values when $d < 1$. The *d* parameter in FIEGARCH model captures long memory in volatility of the data. Hence, the procedure presumes an infinite lag order. Following Bollerslev and Mikkelsen (1996), we fix the lag truncation to 600 for all series except Tunisia where lag truncation is 500. Truncations at lower lag orders might distort the estimation of long term dependences. As in Brunette and Gilbert (2000), we use one lag for estimating ARCH and GARCH terms in the FIEGARCH model. For a well-defined FIEGARCH model, the estimated parameters do not have to satisfy non-negativity constraints.

To account for structural breaks in the ARFIMA model (estimating long memory in first moments) and in the FIEGARCH model (estimating long memory in second moments), we augment equations 3 and 5 as follows:

$$(y_t - \mu) = \varphi(L)\varepsilon_t + \psi(L)^{-1} + [(1-L)^{\phi_2}]^{-1} + \sum_{i=1}^{k} dm_i DUMM \tag{6}$$

$$\beta(L)(1-L)^d \ln(\sigma_t^2) = \omega + \sum_{j=1}^{q}\left(\gamma_j z_{t-j} + \lambda_j\left(|z_{t-1}| - E|z_{t-1}|\right)\right) + \sum_{k=1}^{s} dv_k DUMV \tag{7}$$

In equation (6), *DUMM* represents a dummy variable which takes a value of one before a structural break in the mean returns ($T_{B\text{-mean}}$), and zero otherwise. Likewise, *DUMV* is a dummy variable which takes a value of one before a structural break in variance of returns ($T_{B\text{-variance}}$), and zero otherwise. The rest of the variables are as defined in equations 3 and 5.

4. Empirical Evidence

4.1 Data Characteristics

We begin our empirical analysis with discussing data characteristics reported in Table 1. To facilitate comparison with USA stock returns, we use the US dollar denominated returns for other countries in the sample. The coefficient of variation (CV) indicates risk per unit of return, thus, lower CVs imply better investment opportunities. These statistics show that African stock

Put Table 1 about here

markets offer better investment opportunities relative to the mature US market. Therefore, despite their relatively higher risk of returns (as indicated by high standard deviations), African stock markets adequately compensate investors for higher return. This assertion is supported by the annual Sharpe ratio (risk-adjusted returns) which is higher for each of the African Stock markets compared to the US market.

Low return correlations between each African market and the US market suggest potential diversification benefits for investors. The only exception is South Africa (with a high correlation of 0.631) which is considered a major emerging market. Consistent with stylized facts of stock returns, African markets have fat-tail leptokurtic distribution as shown by excess Kurtosis (Kurtosis >3). Moreover, the robust Jarque and Berra (RBJ) test of Gel and Gastwirth (2008) suggests that the African stock returns exhibit non-normal distributions. The ARCH test of Engle (1982) further indicates that these returns have time-varying variance (heteroskedastic) and the Ljung and Box test suggests they are also serially correlated.

4.2 Some Visual Evidence of Long Memory

Granger and Ding (1995a, b) suggest that absolute returns better capture long memory properties than returns with positive and negative signs. Ding and Granger (1996) argue that variance of stock returns may have long memory properties if the autocorrelations of squared returns exhibit gradual, hyperbolic decay and remain fairly large for long lags. Based on these insights, we attempt to visually identify structural breaks in autocorrelations of squared and absolute returns in the sample. Figure 1 assembles the results for autocorrelations of squared returns, and Figure 2 does the same for autocorrelations of absolute returns.

Put Figures 1 and 2 about here

In most countries, squared returns reveal positive autocorrelations up to 30 or 40 lags and then intermittent switching between positive and negative autocorrelations. However, absolute returns show positive autocorrelations over long periods only for a few countries (Mauritius, Tunisia and USA), while autocorrelations for the rest of countries are episodic, alternating between positive and negative. In sum, while graphical inspections appear supportive of long memory, the visual evidence is unclear.

4.3 Long Memory and Unit Root Tests

We then move to test for the unit root behavior of the African stock markets. Ding *et al*. (1993) demonstrate that when a time series is stationary, shocks decay exponentially to capture short memory; while in non-stationary series, shocks persist infinitely without mean reversion. As to second moments, return volatilities change very slowly over time. Thus, shocks die out at a slow, hyperbolic rate hence exhibiting long memory or long term persistence.

We use two procedures to test for unit root or non-stationary behavior of the return series; namely, the KPSS test of Kwiatkowski, Phillips, Schmidt and Shin (1992) and the PP test of Phillips and Perron (1988). The KPSS test is based on the null hypothesis of trend stationary time series while the null in the PP test is unit root. According to Lee and Schmidt (1996), the asymptotic distribution of KPSS assumes long memory under the null hypothesis hence the dual rejection of stationarity and unit root could be taken to imply the presence of long memory in the return series. As Table 2 suggests, the KPSS test results reject the null of stationarity in levels but fails to reject stationarity in first differences of each series. In contrast, the PP test fails to reject the null of unit root in levels but decisively rejects unit root in first differences. According to Su (2003), the rejection of stationarity in the leveled returns (the KPSS test) and the rejection of unit root in first differenced returns (the PP test) imply the presence of long memory characterized by a hyperbolic decay of the autocorrelation function.

Put Table 2 about here

Having gathered some evidence of long memory using autocorrelation functions and unit root tests, we turn next to discussing structural breaks. Granger and Huang (2004) show that short memory with structural breaks may spuriously reflect long memory. We first investigate the presence of structural breaks in local-currency real returns using Andrews' (1993) and Andrews and Ploberger's (1994) Supremum F (SupF) and Supremum Wald (SupWald) tests. The null hypothesis in these tests is no structural break. We then use the change point model (CPM) of Ross *et al*. (2011) to identify the structural breaking points in the mean and variance of returns[3]. The CPM has three main benefits over other structural breaking point identification models. First, it offers the flexibility to choose between parametric and non-parametric methods. The non-parametric method does not make any assumption about the distribution form of the data. As Table1 indicated, stock returns have excess kurtosis implying heavy-tail distributions. The non-Gaussian distribution of the returns requires the use of non-parametric method to identify structural breaks in mean and variance. The second advantage of the CPM is that it sequentially searches for breaking points thus providing information on both the breaking points and their detection points. And thirdly, the CPM is relatively easier to compute and generates better fit relative to more commonly used techniques as Ross (2013) recently demonstrates.

We assemble the results in Table 3. The results there suggest that only the South African market is free of structural breaks over the estimation period. The rest of the countries exhibit heterogeneous structural break points in the mean ($T_{B\text{-mean}}$) and in variance ($T_{B\text{-variance}}$).

[3] Ross *et al*. (2011) and Ross (2012, 2013) contain lucid discussions on the derivation, explanation and application of the CPM method.

Put Table 3 about here

4.4 Long Memory and the Role of Inflation and Exchange Rates

Prior research on African stock markets ignores the possible effects of inflation and exchange rates on long memory behavior. Long memory in nominal, local-currency denominated, stock returns becomes spurious if they simply reflect long memory of exchange rates when the stock index is constructed in a foreign currency. We compute US dollar- and local currency- denominated stock returns for each of the African markets in the sample to investigate the impact of exchange rates on long memory behavior. The difference in local-currency returns and US dollar returns is attributable to exchange rate fluctuations. Available evidence on this issue for other countries remains largely mixed. While Cheung (1993b) and Lagoarde-Segot and Lucey (2008) find no support for the impact of exchange rates on long memory behavior in several stock markets, Patro and Wu (2004), and Razvan, and Dimitriu (2013) report some evidence to the contrary.

In addition, some studies like Baillie *et al*. (1996) and Baum *et al*. (1999) document long memory behavior of inflation in many countries. If confirmed, then long memory in nominal, local-currency denominated, stock returns is faux since it merely signals long memory of local inflation. However, Cheung and Kon (1995) fail to find significant differences between long memory of nominal and real returns. In light of such confounding evidence on the relation of long memory behavior to changes in inflation and exchange rates, we subject our sample of African stock markets to formal testing of these issues.

To investigate the possibility that long memory simply captures long memory of inflation and/or exchange rates in the African markets, we employ Robinson's (1995) semi-parametric multivariate procedure to test the null hypothesis that d=0 (short memory) against the alternative of d≠0 (long memory). Robinson's multivariate procedure estimates the long memory parameters of multiple series and concurrently provides the corresponding F-statistics for testing the equality of the *d* estimates. We test the following null hypotheses:

$\boldsymbol{H_{01}}$: *d (USA dollar-denominated returns) = d (local currency-denominated nominal returns)*

$\boldsymbol{H_{02}}$: *d (local currency nominal returns) = d (local currency real returns)*

Failure to reject H_{01} (H_{02}) implies that exchange rate (inflation rate) has an insignificant impact on long memory of stock returns. Table 4 (panel A) reports the test outcomes. The results

Put Table 4 about here

suggest the following three inferences. First, we reject the null of $d=0$ (short memory) for markets in Egypt, Mauritius and Tunisia, implying that their stock returns have long memory; while the rest of the markets exhibit short memory processes. Second, the F-statistic for H_{01}(F-stat1) is statistically insignificant across all countries, suggesting that there is no difference in the estimates of long memory parameters using either US dollar-denominated or local-currency denominated returns. And third, the insignificant F-statistic for H_{02} (not reported since all values are insignificant) suggest that long memory using local currency nominal returns and local currency real returns are statistically similar.

Therefore, it can be concluded that inflation and exchange rates have insignificant effects on the long memory behavior of African stock returns. Investors in the African stock markets can thus make inferences using either US dollar- or local currency-denominated nominal returns. Furthermore, we examine whether long memory of US dollar-denominated stock returns of each African market significantly differs from that of US returns. The evidence from F-stat2 in Table 4 suggests that long memory parameters for only Egypt, Mauritius and Tunisia are significantly different from US long memory parameter.

4.5 Dual Long Memory in Mean and Variance and Structural Breaks

Several studies like Lobato and Savin (1998), Ryde´n *et al*. (1998) and Diebold and Inoue (2001) discuss how or why long memory and regime switching may be intimately related. Granger and Huang (2004) argue that occasional breaks slowly generate decaying autocorrelations and other features of the long memory process. Thus, long memory behavior could be partly triggered by neglected breaks in the series. These authors further show that forecasts using models that incorporate occasional break models may generate incremental information regarding future volatility relative to model that ignore structural breaks.

Consequently, we incorporate structural breaks in our analysis of long memory. Specifically, we create dummy variables taking a value of one for observations/dates ($T_{B\text{-mean}}$) before structural breaks in the mean, and zero otherwise. For each country, we use de-thinned local currency real returns and include the dummies in the estimation of long memory parameters by employing the univariate, parametric estimation method.

Semi-parametric methods of estimating long memory (Such as Robinson's test) suffer from two main weaknesses. First, these methods do not account for *AR* and *MA* components. Therefore, short term features of the data generating process are ignored, potentially leading to biased estimates of the long memory parameter, *d* (Agiakloglou *et al*., 1993 and Banerjee and Urga, 2005). Second, semi-parametric methods also require the selection of bandwidth parameters to identify the ordinates. This selection is non-trivial and has incalculable influence on the magnitude and significance of the long memory parameter. To overcome these two challenges, we perform a joint estimation of long memory in the first moment (mean) and second moment (volatility) using the parametric autoregressive fractional integration moving average (ARFIMA) model and the Fractional integrated exponential GARCH (FIEGARCH) model. We call this model ARFIMA-FIEGARCH. This model can concurrently estimate the long memory parameter *d*, as well as short memory components (AR and MA), using the more efficient exact maximum likelihood estimation. Moreover, the FIEGARCH model captures the leverage effects on conditional volatility (negative shocks amplify conditional volatility more than positive shocks of equal magnitudes).

Table 5 present our results from the base ARFIMA-FIEGARCH models without structural breaks. We focus on the long memory parameter estimates ϕ_1 and d_1 for ARFIMA and FIEGARCH models, respectively while ignoring structural breaks. Consistent with the findings using the semi-parametric Robinson test, we find long memory in mean returns for Mauritius and Tunisia, and also in Morocco albeit the evidence there is weaker. For the rest of the countries (Egypt, Kenya, Nigeria and South Africa), short memory parameters proved statistically significant suggesting short term predictability of returns. Therefore, it is possible that sporadic intervals of stable stock returns are extant and have contributed to short memory processes in African stock returns. Interestingly, the results suggest almost an opposite verdict for the US market where both long and short memory parameters [with the exception of *MA (1)*] are all insignificant. This is not surprising since mature markets are more efficient in incorporating distant and immediate information thus meeting the basic threshold of weak form efficiency.

Put Table 5 about here

As to the estimates of long memory in variance (d_1), results in Table 5 indicate that all African stock markets and the US market exhibit long memory since the d_1 estimates are significantly different from zero. This is a robust evidence for persistence of volatility. However, note also that the GARCH terms for Egypt, Morocco, South Africa and Tunisia are statistically significant. Consequently, the evidence of long memory in volatility in these countries may simply conceal periodic short memory or that the significant GARCH terms encapsulate volatility clustering inherent in stock returns. Another noteworthy issue is that countries with higher risk (higher standard deviations of returns) like Egypt, Kenya, Mauritius and Morocco, tend to experience higher persistence of volatility as measured by high estimates for the d_1 parameter. Thus, it appears useful to investigate whether volatility and persistence of volatility are related through a vicious cycle where these countries experience frequent external shocks making return volatility a permanent feature, propagating volatility for many future periods (persistent volatility). Furthermore, with the exception of Morocco, the ARCH terms in the FIEGARCH model are all statistically insignificant suggesting that the FIEGARCH model of long memory is better than the conventional EGARCH and GARCH models.

As we mentioned earlier, results in Table 5 do not account for structural breaks in the mean and variance of returns. We now use equations 6 and 7 to incorporate breaks in ARFIMA-FIEGARCH models and assess the impact of structural breaks on persistence in mean and volatility. We assemble the results in Table 6. Several conclusions emerge from these results.

Put Table 6 about here

Recall first that results in Table 5 suggest that the ϕ_1 long memory (in mean returns) parameters for Morocco, Mauritius and Tunisia were significant without structural breaks. However, when structural breaks are accounted for in Table 6, the ϕ_2 long memory (in mean returns) parameters for these three countries lost their statistical significance. Moreover, the statistical significance of *AR* and *MA* terms for all countries has also dissipated. Thus, according to the results in Table 6, all countries exhibit short memory in returns once structural breaks are incorporated in the testing models. These findings clearly indicate that long memory evidence may simply reflect short memory in the presence of structural breaks. Consequently, inferences on long memory behavior are potentially biased if the testing model ignores regime shifts.

Second, the above conclusion for long memory in mean returns extends to long memory in variance (d_2) parameters. Specifically, as results in Table 6 indicate, long memory in variance parameters found significant in Table 5 for Egypt, Kenya, Mauritius and USA have lost statistical significance upon introducing structural breaks. Therefore, the verdict of long memory in variance for these countries should be overturned to short memory in variance once structural breaks are present in the testing model. For the rest of the countries (Morocco, Nigeria, and Tunisia), their (d_2) parameters improved either in size or in statistical significance.

These results decidedly suggest that the omission of structural breaks is akin to the omission of variables bias which seriously distorts inferences on long memory in mean and variance. To gain further insight on this verdict, we report likelihood ratio statistics in Table 6 testing the null hypothesis that the ARFIMA-FIEGARCH models with breaks (unrestricted models) does not fit the data better than ARFIMA-FIEGARCH models without breaks. Except for Tunisia, this null is firmly rejected which suggests that incorporating structural breaks in the ARFIMA-FIEGARCH model significantly generates superior long memory estimates.

Finally, one might question the adequacy of the ARFIMA-FIEGARCH model. We address this issue by using three different procedures to test the estimated standardized residuals. The test results are reported in Tables 5 and 6. First, we perform the Ljung and Box (1978) test based on the null of zero autocorrelation on standardized residuals. In almost all the sampled markets, we fail to reject the null at various lagged profiles. Second, we perform the ARCH test of Engle (1982) with the null being constant residual variances (homoscedasticity). We fail to reject the null for all countries for various lags. And thirdly, we apply the residual-based conditional heteroskedasticity test of Tse and Tsui (2002). Again, we fail to reject the null of constant variance in standardized residuals. We further note that our models with and without breaks are stationary since d_1 and d_2 parameters are less than one in both estimations. Taken together, these results bolster our use of the ARFIMA-FIEGARCH model for testing long memory in the African stock markets.

5. Conclusion

This paper investigates whether long memory component exists in returns and variance in the case of seven emerging African stock markets along with the mature US market. In addition, the paper uses several procedures to identify structural breaks in the data and explores if such breaks impact long memory inferences. When the testing models ignore structural breaks, the results suggest the presence of long memory in mean of returns in almost half of the sampled markets, and also support long memory in variance in all markets. These findings appear at variance with market efficiency as they imply the predictability of stock returns and their variances, making the African markets ineffective vehicles for mobilizing savings. However, when structural breaks are introduced in the testing models, we find consistent evidence for short memory both in mean and variance across the markets. The message appears loud and clear that failure to account for significant structural breaks in the data can substantially contaminate the evidence on long memory behavior.

References

Agiakloglou, C., P. Newbold, and M. Wohar (1993). Bias in an estimator of the fractional difference parameter, *Journal of Time Series Analysis* 14, 235-246.

Alagidede, P. P. (2011), Return behavior in Africa's emerging equity markets, *Quarterly Review of Economics and Finance*, 51, 133-140.

Ambrose B.W., Ancel E.W., Griffiths M.D. (1993), Fractal structure in the capital markets revisited, *Financial Analysts Journal*, 49, 73-77.

Andrews D.W.K. (1993), Tests for parameter instability and structural change with unknown change point, *Econometrica*, 61, 821-856.

Andrews D.W.K. and Ploberger W. (1994), Optimal tests when a nuisance parameter is present only under the alternative, *Econometrica*, 62, 1383-1414.

Anoruo, E., and Gil-Alana, L. (2011), Mean reversion and long memory in African stock market prices, *Journal of Economics and Finance*, 35, 296-308.

Assaf, A. A. (2007), Fractional integration in the equity markets of MENA region, *Applied Financial Economics*, 17, 709-723.

Banerjee, A. and G. Urga (2005). Modelling structural breaks, long memory and stock market volatility: An overview, *Journal of Econometrics* 129, 1-34.

Baillie, R., T. Bollerslev and H. Mikkelsen (1996), Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics*, 73, 5–59.

Baillie, R. T., Chung C.-F., and Tieslau M. A, (1996), Analyzing inflation by the fractionally integrated ARFIMA-GARCH model, *Journal of Applied Econometrics* 11: 23-40.

Barkoulas, J. T., Labys, W. C., Onochie, J. I., 1999. Long memory in future prices. Financial Review 34, 91-100.

Baum, C. F., J. T. Barkoulas, and M. Caglayan (1999). Persistence in international inflation rates. *Southern Economic Journal* 65, 900-913.

Bollerslev, T. and H. Mikkelsen (1996), Modeling and Pricing Long Memory in Stock Market Volatility. *Journal of Econometrics*, 73, 151–184.

Brunetti, C. and C. L. Gilbert (2000). Bivariate FIGARCH and fractional cointegration. *Journal of Empirical Finance* 7, 509-530.

Caporale, G., and Gil-Alana, L. A. (2003), Long memory and structural breaks in hyperinflation countries, *Journal of Economics and Finance*, 27, 136-152.

Cappelli, C. and Angela, D. (2006), Long memory and structural break analysis of environmental time series, http://www.sis- statistica.org/old/htdocs/files/pdf/atti/Spontanee %202006_203-206.pdf (last access: Aug. 12, 2013).

Cheah Eng, T., and Lee Yoong, H. (2008), A note on the general elections and long memory: evidence from the London Stock Exchange, *Applied Financial Economics Letters*, *4*, 331-335.

Cheung, Y. W. 1993a, Tests for fractional integration: a Monte Carlo investigation, *Journal of Time Series Analysis*, 14, 331–345.

Cheung Y. W. 1993b, Long memory in foreign exchange rates, *Journal of Business and Economics statistics*, 11: 93–101.

Cheung, Yin-Wong and Lai Kon S, 1995, Long memory in international Stock Returns, Journal of International Money and Finance, 14 (4), 597-615.

Diebold, F. X. and Inoue, A. (2001), Long memory and regime switching, *Journal of Econometrics*, 105, 131–159.

Ding, Z., Granger, C.W.J., 1996. Modeling volatility persistence of speculative returns: a new approach, *Journal of Econometrics* 73, 185– 215.

Ding, Z., C. Granger and R. Engle (1993), A Long Memory Property of Stock Market Returns and a New Model, *Journal of Empirical Finance* 1, 83-106.

DiSario, R., Saraoglu, H., McCarthy, J., & Li, H. H. (2008), An investigation of long memory in various measures of stock market volatility using wavelets and aggregate series, *Journal of Economics and Finance*, *32*, 136-147.

Engle, R.F. (1982), Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, *Econometrica*, 55, 391-407.

Fama, Eugene F. and Kenneth R. French, 1988, Permanent and temporary components of stock prices, *Journal of Political Economy* 96, 246–273.

French, K. R., W. G. Schwert, and R. F. Stambaugh (1987). Expected stock returns and volatility. Journal of Financial Economics 19, 3-29.

Gel, Y. R. and J. L. Gastwirth, A robust modification of the Jarque-Bera test of normality, *Economics Letters*, 2008, 99:1, 30-32.

Granger, C.W.J., Ding, Z., 1995a. Some properties of absolute returns: An alternative measure of risk, Annales d'Economie et de Statistique 40, 67– 91.

Granger, C.W.J., Ding, Z., 1995b. Stylized Facts on the Temporal and Distributional Properties of Daily Datafrom Speculative Markets, UCSD Working Paper.

Granger, C.W.J., Ding, Z., 1996. Varieties of long memory models, *Journal of Econometrics* 73, 61–78.

Granger, & Joyeux. (1980), An introduction to long memory time series models and fractional differencing, *Journal of Time Series Analysis*, *1*, 15-30.

Han Young Wook, 2014, Effects of Financial Crises on the Long Memory Volatility Dependency of Foreign Exchange Rates: the Asian Crisis vs. the Global Crisis, *Journal of East Asian Economic Integration* Vol. 18, No. 1 (March 2014) 3-27

Hansen B. (1997), Approximate asymptotic p values for structural-change tests, *Journal of Business and Economic Statistics*, 15, 60-67.

Hays, Rajagopal and Schreiber (2010), Evidence of Long Memory in U.S. Stock Returns: The Case of the 1990s Bubble, *Quarterly Journal of Finance and Accounting*, 49, 5-18.

Hosking, J. R. M. (1981), Fractional differencing, *Biometrika* 68, 165-176.

Kwiatkowski, D.; Phillips, P. C. B.; Schmidt, P.; Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root, *Journal of Econometrics* 54 (1–3): 159–178.

Lagoarde-Segot, T., and Lucey, B. M. (2008). Efficiency from Emerging Markets: Evidence from the MENA region. *Journal of International Financial Markets, Institutions and Money,* 18, 94-105.

Lee, D. and P. Schmidt (1996). On the power of the KPSS test of stationarity against fractionally-integrated alternatives, *Journal of Econometrics* 73, 285-302.

Ljung, G. M. and G. E. P. Box, On a Measure of Lag of Fit in Time Series Models, *Biometrika*,1978, 65:2, 297-303.

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

Lobato, I.N., Robinson, P.M., 1998. A nonparametric test for I(0), *Review of Economic Studies* 65, 475– 495.

McMillan, D. and Thupayagale, P. (2011), Measuring volatility persistence and long memory in the presence of structural breaks: Evidence from African stock markets, *Managerial Finance*, 37, 219 – 241.

Nelson, D. (1991), Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica*, 59, 347–370.

Patro, D. K., and Wu, Y. (2004). Predictability of short-horizon returns in international equity markets. *Journal of Empirical Finance*, 11, 553-584.

Phillips, P. C. B.; Perron, P. (1988). Testing for a Unit Root in Time Series Regression, *Biometrika* 75 (2): 335–346.

Poterba, J. M. and Summers, L. (1988), Mean reversion in stock prices: evidence and implications, *Journal of Financial Economics* 22, 27–59.

Razvan, S. and Dimitriu, R. (2013), *Impact of the foreign exchange rates fluctuations on returns and volatility of the Bucharest Stock Exchange.* Proceedings of the Fifth International Conference on Economics and Administration, (May 2013), 197-209.

Robinson, P.M (1995), Log-Periodogram regression of time series with long range dependence. *Annals of Statistics*, 23, 1048-1072.

Ross G.J. (2012). Modeling financial volatility in the presence of abrupt changes, *Physica A: Statistical Mechanics and its Applications*, 392(2), 350-360.

Ross G.J. (2013), Sequential Change Detection in the Presence of Unknown Parameters, forthcoming, *Statistics and Computing.*

Ross G.J, Tasoulis, D.K, and Adams, N.M. (2011). Nonparametric monitoring of data streams for changes in location and scale, *Technometrics*, 53(4), 379-389.

Ryde´n, T., Tera¨svirta, T., and Sbrink, S. (1998). Stylized facts of daily returns series and hidden Markov model, *Journal of Applied Econometrics* 13, 217– 244.

Sibbertsen, P. (2004), Long memory in volatilities of German stock returns, *Empirical Economics*, 29, 477-488.

Soofi A. S. (1998). A fractional co-integration test of purchasing power parity: The case of selected members of OPEC, Applied Financial Economics, 8: 559–566.

Sowell, F.B. (1992). Maximum likelihood estimation of stationary univariate fractionally-integrated time-series models, *Journal of Econometrics*, 53, 165-188.

Su, J. J. (2003). On the power of the multivariate KPSS test of stationarity against fractionally integrated alternatives, *Applied Economics Letters* 10, 637-641.

Tse Yiu K., Albert, K.C. Tsui (2002). A multivariate GARCH model with time-varying correlations, *Journal of Business & Economic Statistics*, 20 (2002), 351–362

Figure 1: Autocorrelations of Squared Returns

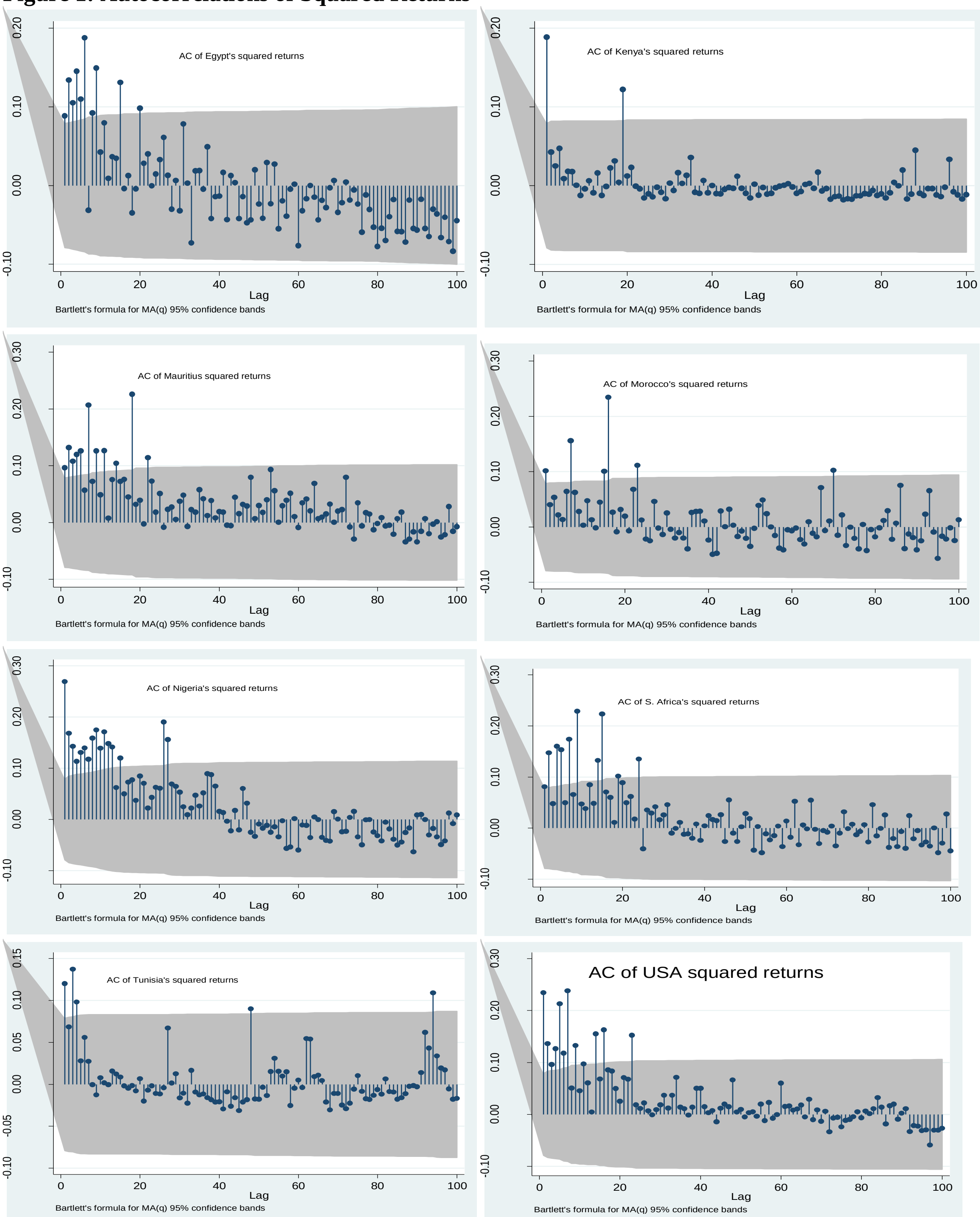

Figure 2: Autocorrelations of Absolute Returns

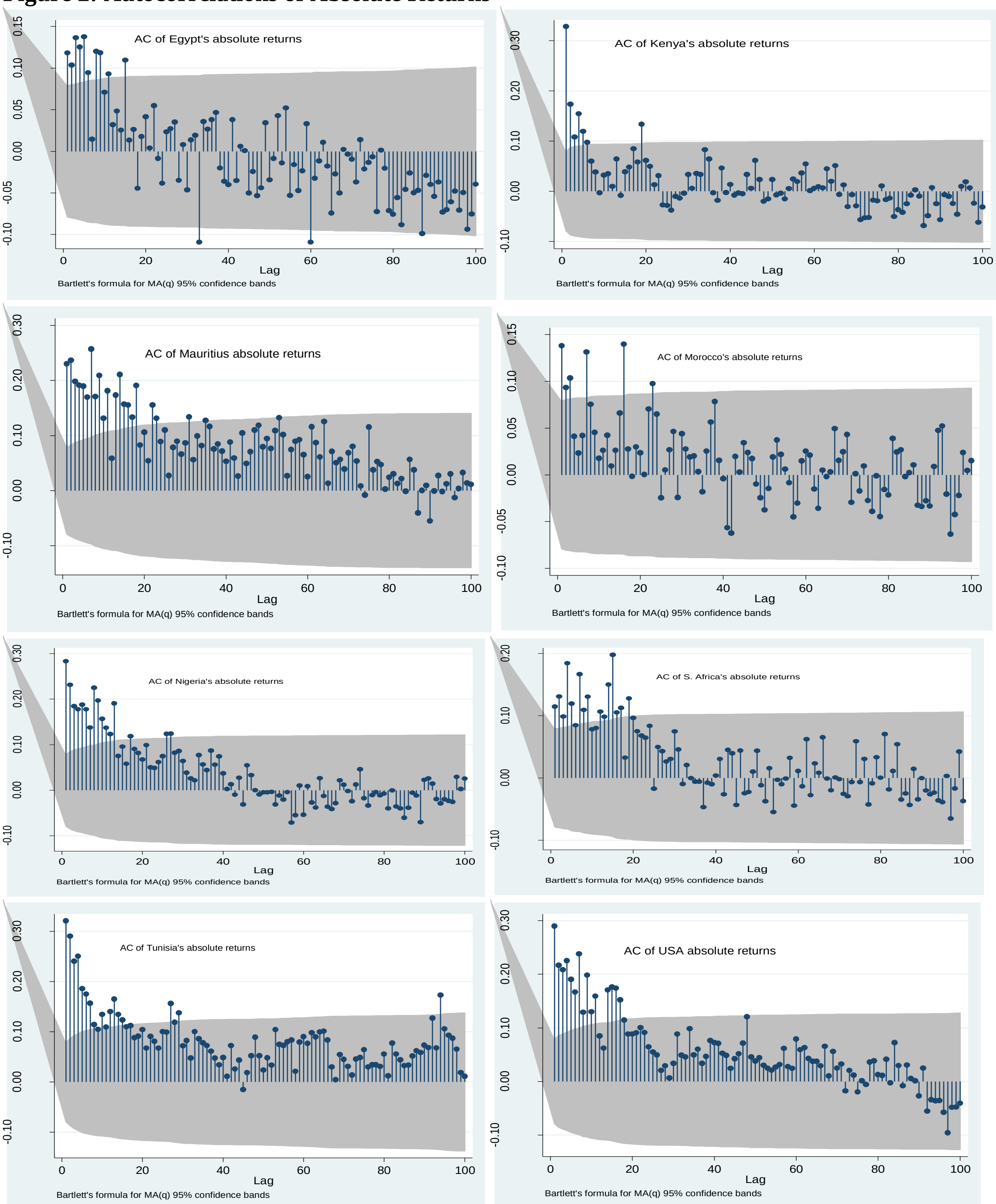

Table 1: Descriptive Statistics (June 5, 2002 – February 26, 2014)

Country	Egypt	Kenya	Mauritius	Morocco	Nigeria	S. Africa	Tunisia	USA
Mean	0.005	0.0047	0.0038	0.002	0.0028	0.0027	0.0018	0.0014
Std Dev	0.043	0.044	0.030	0.028	0.043	0.040	0.025	0.025
CV	9.145	9.245	7.849	15.610	15.345	15.128	14.237	17.658
Sharpe	0.773	0.763	0.842	0.296	0.386	0.382	0.327	0.217
Skew	-0.490	2.243	0.331	-0.023	-0.021	-0.488	0.890	-0.611
Kurtosis	5.642	30.142	9.631	5.964	5.632	6.288	10.454	8.038
RJB	***580.2	***11658.0	***2864.9	***404.0	***424.79	***608.8	***1730.9	***1557.7
Correlation	0.262	0.181	0.111	0.193	0.005	0.631	0.178	
N	613	613	613	613	613	613	509	613
LB(6)	*11.579	***25.108	***10.368	***53.602	**16.604	*13.428	***18.780	***19.445
LB(18)	***37.809	*26.705	**33.949	***142.81	*25.656	***49.784	**29.124	***41.017
LB(36)	***48.487	38.417	***75.030	***152.79	38.698	***70.240	45.575	**56.927
ARCH(6)	***8.079	***4.548	***11.003	***7.543	***19.709	***23.946	**2.592	***11.400
ARCH (18)	***4.084	*1.578	***5.374	***5.646	***8.620	***9.245	0.933	***6.425

Notes: CV is the coefficient of variation. Sharpe is the Sharpe ratio for risk-adjusted annualized returns where we use the risk-free rate of 3.72% for a 20-year US Treasury bond. Correlation is the correlation of between each African stock market and the US stock market based on dollar-denominated returns. *N* is number of weekly observations. RJB is the robust Jarque-Bera test of Gel and Gastwirth (2008). ARCH (6) and ARCH (18) are the autoregressive conditional heteroskedasticity test of Engle (1982) at 12 and 18 lag orders. LB (6), LB(18) and LB(36) are the Ljung-Box serial correlation test of Ljung and Box (1978) at 6, 18 and 36 lags of residuals. The sample has 613 weekly observations covering June 5, 2002 to February 26, 2014 for all countries except for Tunisia where the data runs from February 6, 2004 to February 26, 2014. ***, ** and * represent the 1%, 5% and 10% significance level of asymptotically distributed critical values, respectively.

Table 2: Unit Root Test Results

Method	KPSS		PP	
Country	Level	Diff	Level	Diff
Egypt	***1.437	0.137	-1.737	***-24.293
Kenya	***2.129	0.125	-0.696	***-25.166
Mauritius	***2.747	0.084	-1.042	***-23.244
Morocco	***1.571	0.439	-1.422	***-26.670
Nigeria	***0.924	0.128	-1.718	***-25.235
S. Africa	***3.039	0.157	-0.414	***-29.146
Tunisia	***2.542	0.113	-1.759	***-24.961
USA	***1.500	0.231	-0.021	***26.710

Notes: KPSS is the Kwiatkowski, Phillips, Schmidt and Shin (1992) unit root test and PP is the Phillips and Perron test. The KPSS critical values are 0.739, 0.463 and 0.347 at the 1%, 5% and 10% significance levels, respectively. The PP critical values are -3.44, -2.866 and 2.569 at the 1%, 5% and 10% significance levels, respectively.

Table 3: Identifying Structural Breaking Points

Country	SupF	SupWald	$T_{B\text{-mean}}$	$T_{B\text{-Variance}}$
Egypt	***12.127	***24.253	04/21/2008	12/23/2002
				09/29/2008
Kenya	***23.229	***43.459	02/09/2004	02/16/2004
			06/02/2008	05/03/2004
			02/23/2009	08/25/2008
				03/23/2009
				12/24/2012
Mauritius	**5.526	**13.051	02/18/2008	11/20/2006
			03/02/2009	09/07/2009
				11/28/2011
Morocco	***13.867	***27.733	03/10/2008	12/26/2005
				07/24/2006
Nigeria	***16.395	***32.789	03/03/2008	09/20/2002
			01/26/2009	07/17/2006
				05/19/2008
				09/21/2009
S. Africa	4.377	8.754	N/A	01/16/2006
				09/29/2008
				05/18/2009
Tunisia	*4.533	*9.066	11/28/2005	02/06/2006
				01/24/2011
				03/07/2011
USA	*4.788	6.77	07/22/2002	11/25/2002
			06/07/2004	06/30/2003
				07/16/2007
				09/01/2008
				09/14/2009

Notes: SupF and SupWald are the Andrews (1993) Maximum F-statistics for structural breaks test based on the null of no structural break. $T_{B\text{-mean}}$ is the structural break point of the mean returns while $T_{B\text{-Variance}}$ is the structural break points for the unconditional variance. ***, ** and * shows statistical significance at 1%, 5% and 10%, respectively.

Table 4: Long Memory, Exchange Rates, Inflation Rates and Structural Breaks

Panel A	Currency	*d*	Std. error	t (Ho: d=0)	P-value	F-stat1	F-stat2
Egypt	US dollar	0.0825	0.0368	**2.243	0.026		*2.819
	Local	0.0715	0.0368	*1.944	0.053	0.049	
Kenya	US dollar	-0.0158	0.0344	-0.460	0.646		0.040
	Local	-0.0140	0.0344	-0.407	0.684	0.004	
Mauritius	US dollar	0.0916	0.0355	***2.582	0.010		*3.466
	Local	0.0537	0.0355	1.514	0.131	0.570	
Morocco	US dollar	0.0130	0.0394	0.331	0.741		0.130
	Local	0.0047	0.0394	0.118	0.906	0.023	
Nigeria	US dollar	0.0439	0.0360	1.217	0.224		0.960
	Local	0.0231	0.0360	0.641	0.522	0.166	
S. Africa	US dollar	-0.0286	0.0368	-0.775	0.439		0.200
	Local	-0.0477	0.0368	-1.296	0.196	0.136	
Tunisia	US dollar	-0.1009	0.0375	***-2.691	0.008		*3.101
	Local	-0.0769	0.0375	**-2.050	0.041	0.205	
USA	US dollar	-0.0057	0.0364	-0.156	0.876		
Panel B							
Egypt	Local real	0.0726	0.0431	1.6847	*0.0930		
Kenya	Local real	-0.0062	0.0466	-0.1329	0.8940		
Mauritius	Local real	0.0559	0.0461	1.2117	0.2260		
Morocco	Local real	0.0061	0.0454	0.1346	0.8930		
Nigeria	Local real	0.0233	0.0459	0.5082	0.6120		
S. Africa	Local real	-0.0350	0.0382	-0.9165	0.3600		
Tunisia	Local real	-0.0614	0.0483	-1.2730	0.2040		
USA	Local real	-0.0057	0.0463	-0.1231	0.9020		

Notes: F-Stat1 tests the null hypothesis d1=d2 for 1=US dollar denominated returns and 2=local currency denominated returns. F-stat2 tests the null hypothesis that dollar denominated d estimated for each country=d estimated for USA. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

Table 5: Long Memory in Mean Returns and Volatility without Structural Breaks

Panel A: ARFIMA	Egypt	Kenya	Mauritius	Morocco	Nigeria	S. Africa	Tunisia	USA
ARMA	(2,2)	(1, 0)	(0,0)	(1,0)	(1,1)	(2,1)	(1,0)	(2, 2)
Constant	***0.631	0.397	0.174	0.091	0.217	***0.408	-0.015	***0.232
ϕ_1	0.161	0.001	***0.099	*0.091	-0.126	0.042	***0.053	0.017
ψ_1 *=AR(1)*	***0.279	0.043		-0.099	***0.813	***0.789	***-0.093	-0.746
ψ_2 *=AR(2)*		***0.282				0.091		0.118
φ_1 *=MA(1)*	**-0.429				***-0.649		***-0.917	*0.637
φ_2 *=MA(2)*		***-0.258						-0.220
Panel B: FIEGARCH								
Constant	*0.475	**0.471	*0.381	***0.921	***1.061	*2.418	***1.683	***1.226
d_1	***0.919	***0.801	***0.877	**0.666	***0.607	*0.422	**-0.436	***0.627
ARCH	0.184	-0.188	-0.513	**-0.508	-0.074	-0.164	1.728	0.088
β *=GARCH*	***-0.609	-0.031	0.286	**0.563	0.269	***0.730	***0.937	0.236
γ *(sign)*	-0.046	0.001	0.033	-0.048	-0.048	-0.077	0.022	***-0.272
λ *(size)*	***0.388	***0.627	***0.380	***0.334	***0.403	**0.147	**0.272	**0.142
G.E.D.(DF)	***1.256	***1.153	***4.041	***1.373	***1.311	***1.655	***1.160	***1.603
Panel C: Diagnostics								
LB(5)	2.020	0.615	3.525	3.212	2.437	3.402	**8.695	3.558
LB(10)	6.459	8.325	5.058	3.937	4.773	8.225	11.771	5.937
LB(20)	10.335	15.197	7.257	12.500	17.795	18.159	16.533	14.764
ARCH(2)	0.244	0.168	0.703	0.211	0.259	1.246	0.199	0.612
ARCH (5)	0.452	0.216	0.685	0.667	0.462	0.661	1.678	0.858
ARCH (10)	0.600	0.744	0.476	0.467	0.446	0.778	1.212	0.642
RBD (2)	***65.385	0.858	3.482	0.412	1.370	0.123	0.398	1.444
RBD(5)	-1.584	0.808	*9.875	4.684	2.736	-3.620	0.751	***27.824
RBD (10)	5.003	**19.827	**21.641	***32.816	4.016	-1.183	3.015	7.454

Notes: LB(i) for i=5, 10, and 20 is the Ljung Box test of Ljung and Box (1978) whose null hypothesis is zero correlation of residuals. ARCH (j) for j=2, 5 and 10 lags is the Autoregressive conditional heteroskedasticity LM test of Engle (1982) whose null is constant variance (homoscedasticity). G.E.D is the generalized error distribution (degrees of freedom) which captures the distribution of the tail. RBD is the residual-based diagnostic of conditional heteroskedasticity of Tse (2002) at 2, 5 and 10 lags. ***, ** and * indicates statistical significance at 1%, 5% and 10% significance level.

Table 6: Long Memory in Mean Returns and Volatility with Structural Breaks

Panel A	Egypt	Kenya	Mauritius	Morocco	Nigeria	S. Africa	Tunisia	USA
ARMA	(2,1)	(0,0)	(1,1)	(1,1)	(0,0)	(1,0)	(2,1)	(1,1)
Constant	0.190	***0.435	0.052	-0.178	0.348	**0.195	-0.090	**0.199
dm_1	*0.720	**1.083	2.019	***0.605	***2.025		-0.025	***-3.236
dm_2		1.594	***-1.736		***-1.993			0.241
dm_3		-1.749						
ϕ_2	-0.029	0.024	0.057	-0.058	0.037	-0.024	0.161	-0.034
ψ_1 =*AR(1)*	-0.102		0.013	0.385		*-0.107	-0.198	-0.135
ψ_2 =*AR(2)*	0.071						-0.113	
φ_1 =*MA(1)*	0.155		-0.005	-0.345			0.004	0.019
Panel B								
ω	***2.735	***2.593	**1.234	**0.987	**1.540	***1.361	*1.098	***1.361
dv_1	-0.668	**-1.624	-1.239	***-1.653	***2.108	***-0.515	-0.932	***0.734
dv_2	***-2.346	***1.912	***1.447	0.806	-0.731	***-0.916	-1.417	***1.218
dv_3	***2.462	***-2.036	1.149		*-1.178	***1.854	***2.544	***-0.655
dv_4		***2.516			***2.440			***-1.511
dv_5		***-0.842						***1.447
d_2	0.190	-0.077	0.513	***0.815	***0.812	**0.321	***0.497	0.026
ARCH	-0.477	***1.028	-0.461	**0.697	-0.027	**-0.445	1.056	0.266
β =*GARCH*	0.852	**-0.419	*0.636	***-0.960	*-0.262	**0.456	0.250	**0.649
γ *(sign)*	-0.015	0.133	0.049	**-0.110	-0.012	***-0.309	0.056	***-0.305
λ *(size)*	0.254	*0.284	0.266	***0.360	***0.317	0.010	**0.249	-0.048
G.E.D.(DF)	***1.362	***1.114	***1.149	***1.281	***1.292	***2.229	***1.125	***1.902
Panel C								
LB(5)	4.735	1.929	2.878	8.667	2.734	*6.277	**9.053	0.993
LB(10)	8.766	3.559	4.0254	10.558	3.706	10.07	11.69	5.593
LB(20)	17.808	9.784	6.092	15.915	19.84	**32.835	16.24	19.12
ARCH(2)	0.862	0.02	0.484	**3.852	0.263	0.277	0.191	0.219
ARCH(5)	0.980	0.38	0.554	0.256	0.526	1.225	1.719	0.186
ARCH(10)	0.837	0.339	0.38	0.374	0.356	1.012	1.13	0.548
RBD(2)	2.197	0.021	2.845	-3.567	0.322	1.151	0.104	0.669
RBD(5)	-7.714	6.192	6.134	6.132	4.822	-6.79	-1.75	0.31
RBD(10)	6.844	13.97	10.034	1.624	6.700	2.003	1.238	2.453
LR	***31.52	***188.62	***16.48	***14.10	***20.10	***35.37	0.44	***43.02

Notes: LR is a likelihood ratio computed as: LR= 2[L (θ_1) – L (θ_0)], where L (θ_1) and L (θ_0) are the log likelihood of the unrestricted and restricted models, respectively. dm_i (i=1, 2, 3) denotes the dummy variable capturing structural breaks in mean returns while dv_j (j=1, 2, 3, 4, 5) denotes the dummy variable capturing structural breaks in the variance of returns. See Table 5 for the definitions of other terms.