Regionalization versus internationalization of African stock markets: A frequency-time domain analysis

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Abstract

This paper examines regional and global co-movemnt of Africa's stock markets using the three-dimensional continuous Morlet wavelet transform methodology. The analyses which are done in segments investigate co-movements with global markets; bilateral exchange rates expressed in US dollars and euro; and four regional markets in Africa. First, we find evidence of stronger co-movements broadly narrowed to short-run fluctuations. The co-movements are time-varying and commonly non-homogeneous – *with phase difference arrow vectors implying lead-lag relationships.* The presence of lead-lag effects and stronger co-movements at short-run fluctuations may induce arbitrage and diversification opportunities to both local and international investors with long-term investment horizons. The findings also reveal that some African equity markets are, to a degree, segmented from volatilities of the dollar and euro exchange rates. Thus, inferring that international investors may diversify their portfolio investments across those markets without worrying about the effects of currency price volatility.

Key words: wavelet coherency, African stocks, volatilities, co-movement, exchange rates, diversification.

JEL Classification Codes: C40; F36, G11, G15

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1   Introduction

Among other factors, with an anticipated human population growth of about 1.458 billion by 2025 (World Bank, 2014)[1], Africa is increasingly becoming a frontier for investment and world economic development.[2] Increases in demographic transitions opens a window of opportunities, as the working age population increases. This presents an opportunity to open up the African market to enhance intra-African trade, as well as the flow of capital across borders and between Africa and the rest of the world over time. Recent trends in African total trade flows – exports and imports, highlight a shift in trade dynamics and increasing competition from China for the African market (AfDB, OECD, UNDP, 2015). From 2010 to 2013, intra-African exports grew by 50% and by another 11.5% in 2014 to USD61.4 billion. Despite Europe's dominance in African trade, Africa's trade with Asia rose by 22% between 2012 and 2013. Moreover, since 2000 official remittances to Africa increased six-fold and were projected to reach USD64.6 billion in 2015 with Egypt and Nigeria receiving the bulk of flows. At the same time, increasing Greenfield investments from China, India, and South Africa are expected to increase foreign investment in the continent. The resultant effects of these are improvements in the overall economic growth and developments in the financial sector. In fact, Ahmed *et al.,* (2014) estimates the contribution of Africa's demographic dividend to gross GDP volume growth of 10-15% by 2030.[3] Standard economic theory postulates that the flow of foreign capital to a recipient country increases its stock of capital and technological knowledge, leading to better economic performance. Capital flows could also enhance local savings, promote capital accumulation, and market efficiency.

To reap the above benefits, African countries ought to establish stronger ties and collaborations with the global economy. However, the degree and extent of both inter- and intra-regional interconnectedness ought to be pegged at certain optimal levels in order to reap benefits from scale economies.[4] In the past three decades, efforts at integrating Africa regionally and globally have been aggressively pursued, albeit with some challenges. For instance, Africa has managed to significantly attain progress in economic integration including progressive development of regional infrastructure and removal of some barriers to intra-regional trade (Mougani, 2014). Despite this, progress in economic convergence, as well as, monetary coordination and financial sector integration remains slothful (Mougani, 2014). At the same time, lessons from the Eurozone suggest that efforts at attaining economic convergence can better be enhanced

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[1]https://africacheck.org/factsheets/factsheet-africas-population-projections/

[2]Bodenhorn and Cuberes (2010) establish positive correlation between financial development and city growth robust to controls for city geographical characteristics, percentage of population working in different sectors, and initial population of a city.

[3]*Unless otherwise stated, figures are gleaned from AfDB, OECD, UNDP (2015) African Economic Outlook report.*

[4] *Though highly integrated markets may present fertile grounds for shock spillover the benefits of integration cannot be overemphasized. An aggressive pursuit of integration will not only help in risk diversification but also help smooth the impact of shocks – Beck et al., (2009).*

on the wheels of prior monetary coordination and sufficient levels of financial integration, regionally and globally. In African Development Bank's (AfDB) 2014 Policy Paper on the continent's Regional Integration, Litse and Mupotola (2014) recommend that the Eurozone model of economic convergence should incite African Regional Economic Communities (RECs) to adopt measured and thoughtful approaches towards integration by meeting some basic conditions including financial sector integration.

The call to ensure stronger ties of the African financial sector regionally and globally has attracted various scholars to empirically examine the level and extent of co-movements and integration of African financial markets. In Africa, among the studies that have investigated the linkages between domestic and/or regional and global financial markets, as well as various economic variables are Pukthuanthong and Roll (2009), Alagidede (2010), Ntim (2012), Abdullahi and Mmolainyane (2014), Moss and Thuotte (2013), Chinzara and Kambadza (2014), Motelle and Biekpe (2015), etc. These studies highlight the avenues for economic development, risk reduction, markets efficiency and enhancement, portfolio diversification, and financial stability.[5] Whilst the above studies make significant contribution to the literature on African financial markets inter-linkages with the rest of the world, their contribution to exploring regional dynamics in stock markets co-movements, as well as drawing useful and practical inferences for short-term and long-term investors appears lacking. Thus, this paper fills the gap with more flexible and localized co-movements analysis. The method employed also allows for an assessment of the impact of investment horizon. From the point of view of portfolio diversification, short-term or long-term investors are more concerned with the co-movements at higher or lower frequencies to help them formulate their investments strategies. Thus, we are able to make a distinction between the short-term and long term investor, as well as their investments horizons.

Despite the considerable efforts by extant studies to examine the nature and/level of African stock markets' co-movement, some significant gaps still exist to warrant further research attention. First, estimation methods adopted by the cited references fail to capture co-movement within the frequency-time spectrum capable of aiding in the formulation of investment strategies that take into account the needs of the short-term and long-term investor. Second, it is not clear at the moment, the nature of regional co-movements of the African stock markets. Third, the role played by the 2007-2009 global financial crisis (GFC) in moderating regional and global co-movements of equity markets in Africa has not been profoundly investigated. Meanwhile, such development is likely to affect the level of cross-border listings of stocks and liquidity in the financial system with consequential effects on co-movements. On the basis of the above, this paper examines African stock markets co-movement, regionally and globally over time. Particularly, the results are expected to identify the regional or global market that has the strongest linkages with markets in Africa, and the nature of the linkages. Additionally, the periodicity of the mar-

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[5] *It is important to stress that results from these studies are not uniform.*

ket nexus is investigated to account for the presence of any significant and/or persistent business/market cycles characterizing the intensity of cross-market co-movements. Such analyses may have useful implications for hedging and diversification strategies of investors, as well as for policy makers in surmounting the conundrums of Africa's financial markets integration agenda and shaping policy responses towards coordinated and independent financial markets.

The paper contributes to the existing literature in different perspectives. First, converse to studies that analyze co-movement within one asset market, we are keen in investigating whether co-movement exists within same and among different asset classes. Thus, we examine co-movements of: (i) related regional or global stock markets (thus market-to-market co-movement), (ii) stock and commodities markets (market-to-commodities co-movement), (iii) stocks and currency markets (markets-to-currency price co-movement). The concept of commodity 'financialization'[6] underscores the need for the inclusion of commodities in a diversified portfolio with stocks since commodities show equity-like returns and low correlation with traditional assets (Gorton and Rouwenhorst, 2006). Additionally, since currency price changes interact with stock prices through either the portfolio balance theory or international trade oriented model, examining the dynamic nexus between currencies and stock returns is very useful for fund managers and market participants. In fact, Bekaert and Harvey (2014) recommend for the inclusion of new sub-segments such as currencies and bonds in related studies. With the inclusion of such new sub-segments, it is expected that co-movement may be detected even when the equity markets of two economic blocks are not directly linked together. The challenge associated with the approach by previous studies is that, the scope for co-movement becomes limited for both diversified and undiversified markets. Thus, we argue that the reliance on only stock markets' data-sets to model co-movement may be necessary but not sufficient condition.

Second, in contrast to earlier related studies in Africa, we examine the co-movement of equity markets volatilities (see similar approaches in, Nikkinen *et al.*, 2006; and Graham & Nikkinen, 2011). The rationale is that volatility quantifies the risk of a stock market, and therefore, is relevant to portfolio managers when rebalancing their portfolios from one market to another (Graham and Nikkinen, 2011). This logic is more grounded following the advent of the 2007-2009 global financial crisis (GFC) that heightened market uncertainties and price fluctuations. Reaction of market participants differ in periods of high and low market volatilities affecting the overall informational flow, cross-market listings, markets microstructures, and the degree and nature of co-movements. The results therefore may provide risk managers and policy makers with deeper comprehension of equity markets dynamics across geographical regions, thus helping them in devising effective hedging strategies. This makes our results robust to existing ones on African markets co-movements.

Methodologically, we employ the wavelet estimation technique (which, to

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[6] *The process of speculative market participants' consideration of commodities as investment assets is referred to as the "financialization" of commodities.*

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the best of our knowledge has not seen substantial application in this area of research, particularly, on Africa stock markets). This constitutes a significant advancement in the empirical studies on emerging equity markets co-movements. The strength of the wavelet analysis relative to other models such as correlation, ARCH and GARCH, and standard Granger causality or cointegration analysis is its localization in the frequency and time domains, ability to breakdown any ex-post variables on different frequencies to examine the subtleties of joint movements across diverse time horizons without losses in information, and also its capacity to offer a better trade-off between detecting oscillations and peaks or discontinuities.

The remainder of this paper is organized as follows. Section 2 outlines the research design. Section 3 presents data and preliminary results; and Sections 4 and 5 present the results and conclusion respectively.

1.1 Research design

1.1.1 *The continuous Morlet wavelet transforms*

Basically, wavelet transforms are of two categories: the continuous wavelet transforms (CWT) and the discrete wavelet transforms (DWT). Whereas the CWT is useful for extracting features, the DWT is mainly used for noise reduction and data compression (Madaleno and Pinho, 2012). Analyses of co-movements in this paper are done with the CWT with the package (WaveletComp) developed by Roesch and Schmidbauer (2014) – see reference for details of the package and its functionality. The Morlet wavelet allows for good identification and isolation of periodic signals, by providing a balance between localization of time and frequency (Grinstead *et al.,* 2004), and also appears to provide a better trade-off between detecting oscillations and peaks or discontinuities. The Morlet wavelet, a plane wave modulated by Gaussian can be expressed in the simplest form as:

$$\varphi\left(\eta\right) = \pi^{-\frac{1}{4}} e^{i\,\eta\,\psi} e^{-\frac{\eta^2}{2}}, \tag{1}$$

where, η is non-dimensional 'time' parameter. The "angular frequency" ψ (or rotation rate in radians per unit time) is set to 6 to generate the admissibility of the Morlet function. The period or inverse frequency measured in time units is equal to $2\pi/6$, since one revolution equals 2π (radians). $\varphi\left(\eta\right)$ is complex, nonorthogonal, and normalized to have unit energy.

For proper examination of the time-varying relationship between two time series, we apply the bivariate concept called the wavelet coherence. A better definition of the wavelet coherence can be attained by considering the cross-wavelet transform and wavelet power spectrum and phase difference. The concept of cross-wavelet analysis provides appropriate tools for (i) comparing the frequency contents of two time series, (ii) deriving conclusions about the synchronicity of the series at specific periods and across certain ranges of time – see Roesch and Schmidbauer (2014). The cross-wavelet transform is able to decompose the Fourier co- and quadrature-spectra in the frequency-time domain. Defined by Torrence and Compo (1998), the cross-wavelet transform (XWT)

of two time series x_t and y_t can be specified as: $W^{xy} = W^x W^{y*}$; where W^x WaveletComp implements the rectified version given as:

$$W^{xy}(s, \tau) = \frac{1}{\tau} . W^x(s, \tau) . W^{y*}(s, \tau) \tag{2}$$

where s and τ respectively refer to frequency and time. The modulus of equation [2] can be construed as cross-wavelet power – assessing the similarity of the two series' wavelet power in the frequency-time domains (Roesch and Schmidbauer, 2014). It also shows the areas in the time-frequency space where the time series depicts a high common power, i.e. it denotes the local covariance between the time series at each scale (Vacha and Barunik, 2012). The cross wavelet power (P) is given as:

$$P^{xy}(s, \tau) = |W^{xy}(s, \tau)| \tag{3}$$

Similarly, in a univariate framework, the power spectrum of each wavelet transform can be taken as the modulus of that wavelet transform. Thus the power spectrum of x is $|W^x|^2$. It depicts the distribution of the energy (spectral density) and local variance of a time series across the two-dimensional frequency-time space leading to a frequency-time representation (see also Torrence and Compo, 1998; and Madaleno and Pinho, 2012; for deatails).

The phase for wavelet depicts any lead/lag linkages between two time series, and can be defined as:

$$\theta_{xy} = \tan^{-1} \frac{I\{W_t^{xy}\}}{\Re\{W_t^{xy}\}}, \qquad \theta_{xy} \in [-\pi, \pi] \tag{4}$$

An absolute value of θ_{xy} less (larger) than $\pi/2$ indicates that the two series move in phase (anti-phase, respectively) referring to the instantaneous time as time origin and at the frequency under consideration, while the sign of the phase shows which series is the leading one in the relationship. In the graphical plots, the phase vectors are shown by arrows.

Similar to Fourier coherency which measures the cross-correlation between two time series as a function of frequency, wavelet coherency is also considered as the equivalence of correlation coefficient, though there are significant differences between them (see Madaleno and Pinho, 2010, pp. 12). Wavelet coherency requires smoothing of both the cross-wavelet spectrum and the normalizing individual power spectra. In line with Torrence and Webster (1999), we define the wavelet coherence of two time series x and y as:

$$R_t^2(s) = \frac{|S(s^{-1}W_t^{xy}(s))|^2}{S(s^{-1}|W_t^x(s)|^2) . S(s^{-1}|W_t^y(s)|^2)} \tag{5}$$

where S is a smoothing operator. It can be noticed that the definition in equation [5] mimics the traditional correlation coefficient, and it is useful to think of the wavelet coherence as a localized correlation coefficient in the frequency-time space (Madaleno and Pinho, 2010; Tiwari *et al.*, 2014). Wavelet

coherence near one shows a higher similarity between the time series, whilst coherence near zero depict no relationship.

2   Data and preliminary analysis

Analysis in the paper cut across different market classifications namely: African (frontier),[7] developed, emerging, foreign exchange, and commodities. Data are of daily periodicity and span the period 3rd January 2003 to 29th December, 2014. All data are gleaned from DataStream except the commodities market index which is sourced from Bloomberg. To avoid the effects of non-synchronous trading, the close-to-close method is used to eliminate data points that fall on non-trading or holidays of other markets. All series in the study are analyzed in their volatilities (based on absolute returns computed as the log difference between daily prices or indices). Specifically, the data consist of Morgan Stanley Capital International (MSCI) stock indices of the eight largest African markets: Ghana, Nigeria, South Africa, Botswana, Morocco, Tunisia, Egypt, and Kenya. Additionally, prices of MSCI world index, which comprise developed world markets (hereafter referred to as MSCI developed markets index: (MSCI-DW)), MSCI emerging markets (MSCI-EM) index, Bloomberg Commodities (BCOM) index, and bilateral exchange rates between individual African countries on one hand, and each of the euro and US dollar, on the other hand, are included in the sample. All indices/prices are expressed in U.S dollars, excluding the bilateral exchange rates with the euro. The use of common currency returns in related studies has been justified to be most appropriate in alleviating exchange rate noise (Pukthuanthhong and Roll, 2009).

To examine regional co-movements, all African equity markets with available and reliable data are aggregated into four regions: East Africa, West Africa, Southern Africa, and North Africa. The aggregation is useful due to the structural differences and non-homogeneous nature of regional economic/financial development in Africa, despite significant similarities. Again, Development characteristics of equity markets in Africa are not the same across regions on the continent - see Alagidede, 2008; Ntim *et al.,* 2011 for details of financial markets development in Africa. The aggregation is also to help academics and investors understand better how financial markets development in one region is closely linked with developments in individual domestic markets across the continent. This will provide useful insights on the levels of regional equity market harmonization in Africa.

Regional stock prices/indices (computed as market or value-weighted average prices) are therefore constructed from individual market indices with useful and reliable available data based on a specific geographic distribution. Including a stock from a given market in the regional index may result in upward

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[7] *The following African markets of our sample have the following classifications: South Africa, Egypt, and Nigeria are considered as emerging markets by the IFC (1999) classification. Additionally, Kenya, Morocco (MSCI classification as frontier markets); and currently Ghana and Botswana are being considered as frontier markets by MSCI (Berger et al., 2011).*

bias or idiosyncratic market shocks in the regional index. For this reason, the valued-weighted regional index used for the bivariate estimations with each individual African market i, excludes that market, ostensibly to focus on shocks that are external to each market. Formally, the regional market valued-weighted index/price (p_t) excluding each individual market i, is computed as:

$$p_t = \sum_{t=1}^{T-i} w_{t,j} DPI_{t,j}^q \qquad (6)$$

where, q denotes any other market in the region, except i; $DPI_{t,j}^q$ is the daily price/index of market q in region j; w_t is the weight (which denotes the market capitalization) of each q, and $T=$ total number of markets in a region. w_t is expressed as a fraction of the total market capitalization of all markets in the region. Because market capitalizations are of lower frequencies than daily indices, we use recently available end of year market capitalizations. For countries without current market capitalization observation, the most recently available one is used (consistent with Berger *et al.,* 2011). All market capitalizations data are sourced from World Development Indicators (WDI, 2015), and the websites of the African Stock Exchanges Association (ASEA) and individual country specific stock exchanges.

Tables 1A and 1B present descriptive statistics of returns in volatility of all markets and each bilateral exchange rate respectively. In Table 1A, it is observed that the volatility returns of all individual African markets, as well as regional and global counterparts posted positive mean values during the sample period. The highest (lowest) mean values of 0.01275 (0.00075) are seen with South Africa (North Africa). All sample series have positive skewness and exhibit leptokurtic innovations. The Egypt and East African stock markets possessed the highest and lowest standard deviations respectively. In Table 1B, we note that the highest (lowest) daily mean volatilities of 0.0080 (0.0011) are recorded by the South African rand/dollar and the Egyptian pounds/dollar exchange rates. Similar to Table 1A, the volatilities of all exchange rates are positively skewed and highly peaked. We identify the Botswana pula/dollar and South African rand/dollar on one hand, and the Morocco dirham/euro rates to have respectively the highest and lowest standard deviations.

As a prelude to our examination of co-movements, we examine time plots and follow the work of Zeiles *et al.,* (2003) to investigate the presence of multiple structural breaks/changes of the series, ostensibly to detect common stochastic trends – see also Graham and Nikkinen (2011) and Lee (2004). Figure 1 shows plots of variances of all considered series over the entire span of the data. Since volatilities are based on absolute returns, it is assumed that until certain unexpected changes (probably arising from new information) occurs; the series will continue to exhibit unconditional mean-reversion behaviour in their variances. The variance will return to the stationary mode after the shock and remains so until another unexpected change happens. The plots give an indication of some periodic hikes in the variances of the series over time. Commonly, we observe that with the exception of Botswana and perhaps Ghana, higher amplitudes of

variances are observed for all series between 2008-2009, just around the time of the global financial crisis. For BCOM, MSCI-DW, MSCI-EM, South Africa, and Southern Africa, the variance changes appear relatively normally distributed than in other markets. We also notice some common volatility patterns among the North African markets (i.e. regional and country-specific), excluding Tunisia; and between Nigeria and the West African regional index.

In Figure 2, following the work of Zeileis *et al.*, (2003), we further check the datasets for the presence of multiple structural changes (shocks).[8] In doing so, we initially consider a self-generated linear regression model expressed as:

$$y_i = x_i^| \beta_i + u_i, \quad for \ i = 1, 2, ..., n \quad (7)$$

where; y_i denotes the observation of the response variable at time i; x_i is a $k \times 1$ vector of regressors; β_i is the corresponding vector of coefficients for the regressor; and u_i represent the disturbance at time i. The test detects the presence of multiple shocks by using the regression equation in (7) to verify whether the coefficients remain constant or do not shift severally from a stable regression relationship to another. The latter phenomenon assumes the presence of m change/break points (shocks), where there exist $m+1$ segments in which the coefficients of the regression are constant. To detect the set of breaks/shocks, equation (7) is re-specified as:

$$y_i = x_i^| \beta_j + u_i, \quad for \ i = i_{j-1} + 1 ..., i_j \ and \ j = 1, ..., m+1 \quad (8)$$

where; the m-partition or the collection of shocks represented by $I_{m,n} = \{i, ..., i_m\}$ for which in normal practice $i_0 = 0$ and $i_{m+1} = n$; and j denotes the segment index.

Figure 2 depicts plots of m-segment models for all variables under examination. The optimal model in this case implies selection of the optimal m number of changes (shocks) which are selected using the Bayesian Information Criteria (BIC). *Appendix 1* presents the BIC-based selected optimal number of m-break points, the break point spots and the associated break dates for each variable.

From the results shown in *Appendix 1*, we notice that excluding Botswana, Ghana, Nigeria, and West Africa, which had two volatility changes each, all other markets had three changes. It can also clearly be observed that, most of the volatility shocks (changes) occurred between mid-2007 and 2012. Exceptions are MSCI-EM, Egypt, North Africa, and Morocco where changes started in 2006. Stronger co-movements are therefore expected around these periods. Volatility changes for both African markets and the global markets in 2008 occurred some few months just before the collapse of Lehman Brothers in September, 2008.

2.1 *Empirical results of the wavelet power spectrum, coherency, and phase difference*

Prior to the wavelet analysis, we present results of Pearson correlations of all variables in Tables 2 and 3 to examine the degree of association of African

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[8] *See also Boako et al., (2016)*

stocks with global and regional counterparts, as well as the bivariate exchange rates, and the commodities index. Table 2 shows the correlations of markets with exchange rates whilst Table 3 shows the correlations among markets (that is individual domestic markets, global markets, and the commodities market). Panels A and B of Table 2 respectively show the correlations of all markets with currencies expressed in Euro and US dollars. The results show that approximately 89.8% of the volatility correlations in Panel A are below 0.05 and in Panel B about 87.6% are below 0.05. Thus, both individual country markets, as well, as regional and global markets show low levels of volatility co-movements with the bilateral exchange rates. In contrast to Table 2, we note that 70.8% of the correlation coefficients in Table 3 exceed 0.05; with 96.1% between the North Africa regional market and that of Morocco, 97% between the West Africa regional bourse and Nigeria, and 99.9% between South Africa and the Southern African market. The results show that correlations among stock markets and between stock markets and commodities are stronger than between stock markets and currencies.

Although graphical plots, detection of volatility changes, and Pearson correlations have aided in identifying some levels of co-movements, wavelets are believed to offer superior results. Wavelet analysis is able to derive all information about structural changes in the data through a phase difference technique (Aguiar-Conraria and Soares, 2011). Further, unlike wavelets, the correlation analysis is unable to provide information about when correlations occur and lead-lag relationships - having different data series showing similar periodicities does not necessarily connote lead-lag relationship (Pinho and Madaleno, 2011).

In Figure 3, we employ the wavelet power spectrum (WPS) as a measure of the local variance of the underlying series. The WPS is presented in plots with contours in time and frequency axes indicated on the horizontal and vertical axes respectively. Throughout this paper, time is expressed in years for ease of interpretation. We express frequency in powers of two, ranging from lower, 4 days (bottom of the plot) to upper, 2048 days (top of the plot). In the WPS, thick white contours in regions of energy denote significance at the 5% (95% confidence) level. Following a white noise process, the WPS is estimated from Monte Carlo simulations. To the right of the WPS is a colour bar depicting the steep power gradient of the significant contours ranging from blue (lower power) to red (higher power). The *n-shaped* cone indicates the region of influence affected by edge effects. Periods outside the cone do not represent statistical confidence and are not considered for analysis.

In Figure 3, majority of the variances happen at lower-to-medium frequencies. It is noticed that significantly high variance concentration exist for BCOM between 2004 and 2006; and 2008-2012. The Egyptian stock market shows similar features. These power events appear stronger from early 2008 to late 2009 across the 4-128 day frequency bands. The relatively high power between 2008 and 2009 corresponds with the recent global financial crisis (GFC) that characterized extreme price fluctuations and higher variances in the commodities markets. The WPS plot of MSCI-DW depicts strong significant power effect in the daily frequency band of 4-256 from early 2008 to early 2009. Similar result

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is found at mid-2010 and early 2012. For MSCI-EM, we notice sparingly significant power events from the early parts of 2007 through to beginning of 2008 across the 4-64 day frequency band. An important feature worth mentioning from the WPS plots is that stronger variances are averagely observed around the period of the 2007-2009 GFC. We also notice from all the plots that strong variance concentration is found at low-to-medium frequencies whilst weak variance concentrations are found at relatively higher frequencies.

Though the WPS helps us to identify regions in the distribution of all series where the variances of stock market and commodity indices were higher, it fails to identify co-movement and leadlag relationships capable of determining causality between two series. Possible means of mitigating this shortfall are the resort to wavelet cross power spectrum (WCPS) or wavelet squared coherency. However, we decline the use of WCPS because it can sometimes yield misleading results (Pinho and Madaleno, 2011). Roesch and Schmidbauer (2014) recommend the use of wavelet coherence, rather than WCPS. The wavelet coherence, like the coefficient of determination adjusts for individual (one-dimensional) power difference in two series and provides joint periodic properties of the series (Roesch and Schmidbauer, 2014). Per the nature of our datasets (i.e. having long span over 12 years), it may be worthwhile to examine how co-movements have evolved over time. Again, to be able to make inferences for short and long term investment horizons, it is useful to examine whether or not co-movements vary in the frequency-time domains. To achieve these objectives, we resort to the use of the wavelet squared coherency as a measure of local correlation among our variables; and phase differences to depict any lag or lead relationships between components in the subsequent sub-sections.

2.1.1 *Analysis of global co-movements*

We show the wavelet squared coherency and phase difference between each considered African equity market's volatility of returns with those of developed and emerging stock markets, and the global commodities market in Figure 4. Coherency is shown using contour plots as it involves three dimensions. In Figure 4, the vertical and horizontal axes respectively denote frequency and time with frequency in daily ranges from lower (4 days) to upper (2048 days). The cone of influence showing the region of edge effects contains white contour lines which signify the region of 5% significance level simulated using Monte Carlo method of two white noise series with Bartlett window type. Again, the vertical bar to the right of the coherence and phase difference plots denotes colour codes for local correlations (coherence) ranging from red (high coherence) to blue (low coherence). Thus, in our framework, a red colour inside the white contour at the bottom (top) of the plots represents strong co-movement at low (high) frequencies, whilst a red colour in the white contours at the left-hand (right-hand) side symbolizes strong co-movement at the beginning (end) of the sample period. The phase difference between two series is indicated by arrows. The name

of the index shown first is the first series and the other being the second,[9] on account that the order is needed for the validity of the model (Madaleno and Pinho, 2012). Arrows pointing to the right suggest that the series are in phase. To the right and up means the first series is lagging. Arrows to the right and down means the first series is leading. Arrows pointing to the left mean that the two series are out of phase. To the left and up shows the first series is leading. To the left and down shows that the first series is lagging. Plots of the wavelet squared coherency and phase differences present some exciting results.

A first glance of all the plots shows that there are generally high co-movements across market pairs as the red colour dominates all significant regions. Despite this, most of the stronger and finest coherences stretching over longer periods are found at medium-to-high frequencies. Again, the coherency appears periodic and not spread through the entire time distribution of the data span. It is important to note that some of the coherencies fall outside the region of edge effects (cone of influence) and are therefore not significant. No meaningful inferences can therefore be made from such coherences. From the phase difference arrows, the nexus among markets are predominantly non-homogenous across time because arrow vectors point left and right, and up and down regularly. We in turn analyze individual co-movements in the subsequent paragraphs.

For Botswana, we observe a highly statistically significant co-movement between the Botswana Stock market and BCOM in the 512-1024 daily frequency band for late 2005 to late 2010. The series are in phase with BCOM leading Botswana. At daily frequency bands between 32-256, several co-movements occur throughout the entire period (with non-homogenous phase differences), albeit at short periodicities including the period of the 2007-2009 financial crisis at the 130-256 band (at which period Botswana leads BCOM). Similarly, the co-movement between Botswana and MSCI-DW is very strong at the daily frequency band of 512-1024 from early 2005 to late 2012. During this period, MSCI-DW leads Botswana. However, co-movements observed at early 2007 to end of 2008 at 130-256 bands and between end of 2011 to early 2012 at 65-128 band show Botswana leading MSCI-DW. We notice also higher co-movement between Botswana and MSCI-EM from early 2005 to late 2012 at the 480-1040 frequency band with no lead-lag relationship. Between 2007 and 2008 however, MSCI-EM leads Botswana at the 64-128 band, and between 2010 and 2011, we observe Botswana lagging at the 140-256 band. The strong correlations between the Botswana stock market and those of international markets (BCOM, MSCI-DW, and MSCI-EM) supports the findings of Ahmed and Mmolainyane (2014) that the openness of the Botswana market makes capital market development strongly driven by foreign companies. In the 2007-2009 crisis, lower diamond sales to the financially depressed European markets made Botswana's domestic economy highly vulnerable to shifts in global economies that consume the country's diamond (see also Ahmed and Mmolainyane, 2014). Therefore business cycle fluctuations of international investors consequentially caused sig-

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[9] *For example in the cross coherency plot between Ghana and BCOM, Ghana is the first series and BCOM is the second.*

nificant changes on the Botswana equity market, thereby drawing correlations with global counterparts to unity.

It is important to stress that though significant co-movements exist between Egypt and the markets under consideration, the finest of such co-movements are highly noticeable with BCOM and MSCI-DW. The co-movements of the Egyptian stock market and each of BCOM and MSCI-DW occur at the higher frequency band of roughly 480 to 1000; and stretch over the period of 2005 to end of 2012.

Between Ghana and BCOM, the 5% significant contours depict sparsely stronger co-movements at the 64-130 daily frequency bands occurring at short periodicities. The first noticeable co-movement happens in 2004 with a somewhat non-homogenous phase difference. From early 2007 to late 2008, and between the early periods of 2010 and 2011, we notice separate co-movements in which Ghana leads in the latter case. At a high frequency of 1024, the Ghana-MSCI-DW co-movement (though relatively light) stretches from early 2006 to early 2010 with Ghana lagging. However, towards the middle frequency band (256-508) the co-movement is limited to between early 2008 and early 2012 with Ghana leading. For Ghana MSCI-EM, pockets of higher co-movements with varying phases occur at the 64-510 daily band.

The Kenyan stock market shows stronger co-movements with those of BCOM, MSCI-DW, and MSCI-EM at high frequencies and longer periodicities with some islands of coherency occurring in the middle frequency belts at shorter periods. In all, the Kenya-BCOM and Kenya-MSCI-EM co-movements stretch over relatively longer periods from 2006-2012, whereas for the Kenya-MSCI-DW coherency at the high daily frequency band of 512-1024 starts from late 2008 to late 2010. The phase difference vectors suggest no lead-lag relationship for Kenya-MSCI-EM. In the case of the Kenya-BCOM however, Kenya leads the nexus from late 2006 to early 2009, whilst the part of the coherency occurring between 2009 and 2012 is led by BCOM. Mixed phase difference results are seen for Kenya-MSCI-DW for the 512-1030 frequency band co-movement.

We observe shorter and very thin periodic stronger co-movements of the Casablanca stock market in Morocco with those of the markets under consideration. Mainly, the biggest contours indicating the 5% significance of these co-movements happen at the 128-256 daily frequency bands. For instance, we record stronger co-movement between Morocco and BCOM within year 2011 at the 130-256 band in which BCOM leads. In the case of Morocco-MSCI-EM, stronger co-movement is noticed at the 128-256 daily band from early 2007 to early 2008. It is instructive to note that in the case of Morocco, we do not see any major co-movement with the global markets during the 2007-2009 GFC suggesting some kind of insulation from global volatility shock spillovers of the Casablanca market.

Nigeria generally shows higher degrees of co-movements at high frequencies with the global markets. We notice that from late 2006 to early 2012, the Nigerian stock market index is highly integrated with that of the commodities index (BCOM) at the daily frequency band of 530-1030 with Nigeria lagging. Perhaps due to the oil price boom and bust during the GFC, we ob-

serve stronger co-movements at the 100-150 daily bands from early 2007 to late 2008 in which Nigeria leads. Between 2007 and 2012 at 520-1020 daily bands and from early 2008 to end of 2009 at 128-140 daily bands, Nigeria lags in a stronger co-movement with the MSCI-DW index. Additionally, the longest periodic co-movement of the variance of the Nigeria bourse is seen with that of the MSCI-EM index from early 2007 to early 2013 in which Nigeria leads.

Except for the South Africa-MSCI-EM in which co-movement is in phase, South Africa lags in the co-movement with BCOM and MSCI-DW at the 512-2040 daily frequency bands. At the same frequency bands, co-movements of all the global markets with the South African equity market stretches over longer periods roughly from early 2005 to late 2012. South Africa's integration with the global markets is thus not evolving today. Apart from the above, the South African market also shows stronger co-movement with the MSCI-EM at the 128-256 bands from early 2007 to mid-2008 (with no lead-lag relationship) and from early 2011 to late 2012 (in which case South Africa lags). The strong linkages of the South Africa market with global counterparts may reflect its higher levels of integration, market liquidity, or shocks from the real sector. For example, as noted by Simatele (2014), the effect of the 2007-2009 global financial crisis on South Africa's economy was felt through a deteriorating overall economy which heightened pressure on the country's balance of payment with consequential effects on domestic exchange rates, overall gross domestic product (GDP) and financial sectors, without corresponding increases in portfolio investments flows.

The Tunisian stock market appears to share longstanding cross-market volatility effects with BCOM and MSCI-DW index than with the MSCI-EM index at high frequencies. At the 530-1024 bands, Tunisia leads in the co-movement with BCOM from early 2005 to late 2012. However, at the 512 band, Tunisia lags in its co-movement with the BCOM. At the 512-800 bands, Tunisia leads in the co-movement with MSCI-DW from early 2005 to late 2012. Between Tunisia and MSCI-EM, we do not witness longer periodic co-movements except the islands of high coherencies occurring in 2008 at the 128-240 bands and the co-movement from 2006 to 2008 at the 512-540 daily frequency bands.

In all, co-movement among markets (Africa and global) is dynamic as it is time-varying. The co-movements however, appear partially segmented, as most domestic markets show lower degrees of coherencies with global counterparts at varying periods. The evidence of partial segmentation may reflect low levels of foreign investors' participation in the domestic markets fueled by problems of home bias, high inflation, exchange rate exposures; and other factors such as constraints relating to poor governance structures, macroeconomic unsteadiness, small market sizes, lack of liquidity, political unrest, etc. For instance, despite the increases in private capital flows into Sub-Saharan Africa (SSA) in the early days of the 21st century, the advent of the 2008-2009 global financial crisis (GFC) registered some declines due to increased investor risk-aversion, tighter global credit conditions, and developments in the bond markets (Simatele, 2014). Despite this, the recorded episodes of time varying incremental co-movement towards the end of the data may be explained by aggressive pursuit of integration on the continent. This has been realized through gains in the

removal of some barriers to intra-regional trade, market openness and increased cross-border portfolio capital flows, as well as improvements in overall economic integration.

Interestingly, longer periodic co-movements are felt at higher frequencies. Additionally, short cycle coherencies are also noticed in some cases largely at medium daily frequency bands. Phase difference arrow vectors give indication of lead-lag (non-homogeneous) relationships suggesting negative correlations as in most cases, arrows point left or right, and up and down. Homogeneous arrow vectors indicate positive relationships. We wish to emphasize that lead-lag relationships in cross-market volatility correlations may enhance diversification and arbitrage opportunities worthy of consideration by international investors (Madaleno and Pinho, 2012).

Our empirical results both support and contradict extant literature. Generally, the results support earlier findings on higher integration among international stock markets (e.g. Lee, 2004; Berben and Jansen, 2005, Graham *et al.*, 2012). The generally higher levels of integration of some African markets with global counterparts indicate that most equity markets in Africa are highly vulnerable to international market fluctuations – a precursor for global shock contagion. Again, converse to Graham and Nikkinen (2011) and Graham *et al.*, (2012) in which high degrees of co-movements are recorded at lower frequencies (longer periods) between the MSCI-US and MSCI indexes for emerging markets such as Mexico and Peru, we report strong local volatility correlations between global markets and African stock markets at higher frequencies (short-run fluctuations), with some co-movements at the medium frequencies beyond 2006. Because relatively the finest local correlations occur at higher frequencies – largely 512-1024 days, we argue that cross-market volatility spillovers between global and African markets are confined to short-run fluctuations. This is consistent with Lee (2004) and contradicts Madaleno and Pinho (2012) who respectively argue that the most significant impact in cross-market spillovers are captured at higher and lower frequencies. The differences in our results from other studies may be due to differences in the characteristics of markets considered and the span of data.

Another implication of our finding is that, from the perspective of the international investor, equity portfolio diversification opportunities into African markets (specifically, Tunisia, South Africa, Nigeria, Kenya, Egypt, and Botswana) are relatively less significant in the short term than the long term. International investors with long-term investment horizons could therefore diversify into the above markets to reduce portfolio risk by adopting lower frequency trading strategies. The results generally show that stronger co-movements occurring at medium frequencies exist at shorter periods. This appears useful for investors with short term investment needs seeking diversification in the short-to-medium term.

Further observation of the findings is the somewhat sparse co-movement between the MSCI-DW on one hand and each of Ghana and Morocco on the hand across all frequencies and time. We also notice that relatively major stronger co-movements occurring during the period of the 2007-2009 GFC happen at

higher frequencies (shorter periods). Moving down the frequency axis, major co-movements are hardly observed across all market pairs for the GFC period. This suggests that the impact of the crisis on international investors diversifying their equity portfolio in Africa's stocks was more severe for investors with short-term than those with long-term investment horizons.

2.1.2 *Evidence from regional markets in Africa*

In Figure 5a-d, we report results of individual markets co-movements with regional counterparts. Similar to previous results on wavelet coherency in this paper, relatively major significant co-movements occur at higher frequencies. Exceptions are Morocco vs. North Africa, and probably South Africa vs. Southern Africa, where coherencies are both in the high and low frequencies. Consistent with results from Table 2, we observe that Morocco shows very strong positive co-movements (since all phase difference arrows are in phase) with the North African regional market. This strong correlation moves across the entire time distribution from 2003 to 2014 and at both lower and higher frequencies. Co-movements of all other markets with the North African regional counterpart are relatively sparse.

In East Africa, whereas five markets (Morocco, Egypt, South Africa, Ghana, and Tunisia) sparsely co-move with the regional market, three markets (Nigeria, Botswana, and Kenya) show higher levels of periodic co-movements. Both the Botswana and South Africa stock markets are highly integrated with the Southern African regional market. Botswana's integration with the regional market has evolved over the 2004 to 2012 period at a high daily frequency band of 480-1024. At the middle frequency, however, the co-movement is relatively periodic and not continues. In Table 2, we notice a 99.9% correlation of the South African stock market with the

Southern African regional market along the entire distribution of the series. Figure 5c however indicates that the correlation is time-varying and occurs at high frequencies from 2005 to 2007, whilst between 2008 to early 2012 the correlation revolves around the middle to lower frequency bands. Again, although all other markets outside the Southern African region are highly integrated with the regional market, Kenya and Nigeria are relatively the most integrated. We notice again that markets that are highly integrated with the West African regional counterpart and over longer periods of time are those of Kenya, Botswana, Egypt, and South Africa.

In all, we find evidence of partial segmentation of African stock markets, regionally. The instances of higher regional co-movements among markets may be reflective of the degree of openness and integration, removal of some barriers to intra-regional trade, various market liberalization programmes, as well as level of macroeconomic coordination between countries and regions. Going forward however, aggressive efforts ought to be pursued in the area of harmonizing exchange rate mechanisms, and intensifying trade and other cooperation among national governments to reduce barriers to free flow of investment capital cross regions and countries.

2.1.3 *Co-movements with exchange rates*

Both the international trading effect model (see for example, Aggrawal, 1981; Koulakiotis *et al.,* 2015) and the portfolio balance theory (See for example Frankel, 1983; and Ho and Huang, 2015) suggest the presence of lead-lag relationships between stock markets and exchange rates. As the local currency becomes highly volatile and unpredictable, and the cost of hedging against such uncertainty surges, domestic equity markets may respond in reverse direction through increased competitiveness of local firms arising from positive trade balances and foreign currency current accounts balances – *international trading effect model.* A highly performing local bourse, on the other hand may attract foreign capital flows causing an increase in demand for domestic assets and currency; and vice versa. Increasing aggregate demand for domestic currency relative to a foreign counterpart revalues the domestic currency – *portfolio balance theory.* Whilst the above theories are sound and hold in markets, it is of interest to examine the extent of volatility co-movements across the stocks and foreign exchange (FX) markets over time. The central hypothesis to be tested is that individual country equity market volatilities may influence or are influenced by exchange rate shocks. Already, Fratzscher (2002) suggests that

exchange rate volatility may play an important role in market segmentation. After establishing evidence of partial segmentation in Africa's bourses, Kodongo and Kalu (2011) infer that US dollar – and/or euro investors can diversify their portfolio holdings across Africa's equity markets without bordering about unconditional FX price risk. To test the above hypothesis, wavelet coherence and phase difference plots of volatilities of Africa's stocks and country-specific exchange rates expressed in euros and US dollars are examined for nature and degree of correlation and presence of homogeneous effects (lead-lag relationships).

The plots are shown in Figure 6. Although similar to Figures 4 and 5, the red colour code spreads through the cone of influence, actual regions of significance (as measured by the contours) are scanty. Figure 6a for the co-movement with the US dollar shows that exchange rate volatility has sparse correlation with the volatilities of each of the stock markets in Ghana, and to some extent Nigeria. Despite this, correlations exist between the US dollar and each of the markets of Botswana, Morocco, Tunisia, Egypt, South Africa, and Kenya. Among these, both Botswana and

Morocco have strong positive correlations with the US dollar at the 1024 band, whiles South Africa, Egypt, Tunisia, and Kenya exhibit strong negative relationships each with the US dollar. In the case of the latter relationships, the African markets lead the dollar. In Figure 6b, all markets show relatively some noticeable, albeit scant co-movements (in some cases). The exceptions are Ghana and Botswana which appear not to show any meaningful coherencies with the Euro. In all that, the relationship is negative. It is important to note that co-movements in both 6a and 6b are generally sparse, periodic, non-homogeneous, and occur at higher frequencies (shorter times).

In fact, the evidence of lead-lag (negative) or positive relationships at higher

frequencies (short-run fluctuations) confirms the complex dynamics of the nexus between stock market volatilities and that of exchange rates. In view of the preponderance of the generally scant and negative co- movements, we can infer that most Africa's stock markets are moderately segmented from volatilities of the dollar and euro exchange rates and that international investors may feel comfortable in diversifying their portfolio investments across African stocks without worrying about currency price volatility. This strategy however appears workable for investors with long-term investment horizons since coherencies are largely in the higher frequencies (shorter times).

3 Conclusion

Examining regional and global co-movement of Africa's equity markets, which serves as the subject matter of this paper, may have implications for both portfolio selection and allocation decisions of investors, as well as for policy makers in surmounting the conundrums of Africa's financial markets integration agenda and shaping policy responses towards integrated and independent financial markets. We apply the three-dimensional continuous Morlet wavelet technique to examine regional and global co-movements of African stock markets. The technique is robust to existing measures of co-movement and integration due to is localization in the frequency-time domains and ability to breakdown any ex-post variables on different frequencies to examine the subtleties of joint movements across diverse time horizons without losses in information.

Our results show evidence of stronger time-varying non-homogeneous co-movements of Africa's stocks regionally and globally at higher frequencies (shorter times). Energy concentration of markets variances is however observed to be stronger at lower frequencies. On account of the many noticeable coherencies and lead-lag relationships occurring at higher frequencies, we argue that diversification opportunities may be more practicable for investors operating in the long-term than those in the short-term.

Our findings generally support the literature on increasing co-movements among international equity markets. Also, co-movements with the global commodities index's (BCOM) around the 2007-2009 GFC period was stronger and more noticeable for most African countries (example, South Africa, Nigeria, Botswana, and Kenya) that have large scale trading in one commodity or another. Thus, these markets could not be sheltered from the contagion effects of the global commodities market shocks during the crisis. The results further show evidence of regional co-movemts of some African stock markets. The regional co-movements however, appear slow and weak post 2012. In all cases of regional co-movemnts, regional markets have shown leadership. This reinforces the need for Africa to quicken steps in fostering greater co-operations among markets and develop stronger regional markets. The findings also make it possible to infer that most African stock markets are partially segmented from volatilities of the dollar and euro exchange rates and that international investors may feel comfortable in diversifying their portfolio investments across African stocks without

worrying about currency price volatility. This recommendation however appears plausible for investors with long-term investment horizons since coherencies are largely in the higher frequencies (shorter periods).

By way of extension, future studies could explore regional and international co-movements of Africa's stock markets at the firm level to examine how different firms (low, medium, or high cap) co-move with regional and international counterparts and markets. Again, the periodic nature of the identified co-movements in this paper implies that different global or regional market innovations attract varying responses from Africa's markets over time. Future studies could therefore consider investigating the reasons for such periodic relationships and the kind of business/market cycle events that characterize such co-movements.

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Table 1A: Descriptive statistics of returns (in volatilities)

MARKET	MEAN	MEDIAN	MAX	MIN	SD	SKEWNESS	KURTOSIS
BCOM	0.00840	0.00623	0.06805	5.75E-07	0.00768	2.15808	10.48957
Botswana	0.00475	0.00174	0.16030	0.00000	0.00960	6.59109	71.80905
East Africa	0.00099	0.00062	0.01404	0.00000	0.00125	3.60608	23.68089
Egypt	0.01098	0.00663	0.10872	0.00000	0.01381	2.24040	9.89134
Ghana	0.00475	0.00115	0.12794	0.00000	0.00975	5.08197	41.33031
Kenya	0.00678	0.00457	0.11107	0.00000	0.00799	3.99988	30.78695
Morocco	0.00926	0.00652	0.08724	0.00000	0.00953	2.48508	12.60178
MSCI-DW	0.00693	0.00477	0.17273	0.00000	0.00819	5.70642	80.12100
MSCI-EM	0.00872	0.00620	0.10073	0.00000	0.00960	3.53295	23.50349
Nigeria	0.00938	0.00657	0.10439	0.00000	0.00962	2.56333	15.74459
North Africa	0.00075	0.00049	0.00840	2.30E-07	0.00086	2.87675	15.28979
South Africa	0.01275	0.00940	0.12889	0.00000	0.01273	2.78652	16.66531
Southern Africa	0.01261	0.00912	0.12880	0.00000	0.01260	2.85350	17.25407
Tunisia	0.00508	0.00379	0.06357	0.00000	0.00494	2.88441	18.95112
West Africa	0.00871	0.00644	0.07935	0.00000	0.00819	2.33077	13.01315

The table shows descriptive statistics for the African stock markets as well as regional and global markets in volatilities, from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.

Table 1B: Summary statistics of bilateral exchange rates expressed in Euros (€) and US Dollars ($)

	Botswana		Egypt		Ghana		Kenya		Morocco		Nigeria		South Africa		Tunisia	
	€	$	€	$	€	$	€	$	€	$	€	$	€	$	€	$
Mean	0.0058	0.0061	0.0048	0.0011	0.0062	0.0037	0.0057	0.0033	0.0012	0.0037	0.0059	0.0029	0.0070	0.0080	0.0028	0.0035
Median	0.0044	0.0044	0.0036	0.0004	0.0045	0.0016	0.0041	0.0018	0.0008	0.0028	0.0041	0.0009	0.0053	0.0062	0.0015	0.0026
Maximum	0.1160	0.1196	0.1584	0.1551	0.1218	0.0654	0.0622	0.0556	0.0171	0.0616	0.1163	0.1198	0.0822	0.0922	0.1014	0.0315
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Std. Dev	0.0061	0.0075	0.0051	0.0035	0.0072	0.0061	0.0057	0.0046	0.0013	0.0034	0.0069	0.0066	0.0066	0.0075	0.0074	0.0032
Skewness	5.7591	5.3404	10.0758	29.1408	5.4785	3.9428	2.5539	4.0047	3.9301	2.9670	4.7548	6.5630	2.3559	2.4331	10.2898	2.0871
Kurtosis	79.778	57.676	275.037	1213.476	59.425	24.399	14.427	28.088	31.533	34.125	46.437	66.781	13.882	15.243	119.536	11.5992

The table shows descriptive statistics for the bilateral exchange rates expressed in Euros (€) and US Dollars ($) in volatilities, from 3ʳᵈ January, 2003 to 29ᵗʰ December, 2014. Volatilities are based on absolute returns.

Table 2: Correlations of markets with bilateral exchange rates

Markets	Panel A: Bilateral exchange rates expressed in Euros (€)							
	Botswana	Egypt	Ghana	Kenya	Morocco	Nigeria	South Africa	Tunisia
Botswana	0.0049	-0.0228	-0.0168	-0.0024	-0.0275	-0.0336	-0.0021	-0.0422
Egypt	0.0465	0.0084	-0.0025	0.0262	0.0416	0.0370	0.0457	-0.0122
East Africa	-0.0016	-0.0274	-0.0168	-0.0253	-0.0097	-0.0172	0.0102	-0.0355
Ghana	0.0205	0.0073	0.0147	0.0029	0.0135	-0.0208	0.0392	-0.0046
Kenya	-0.0001	-0.0232	-0.0544	-0.0505	-0.0162	-0.0321	-0.0273	0.0134
Morocco	-0.0181	-0.0441	-0.0235	-0.0002	-0.0579	-0.0308	-0.0306	-0.0105
Nigeria	-0.0086	-0.0364	-0.0106	-0.0222	-0.0373	-0.0356	-0.0179	-0.0334
North Africa	-0.0231	-0.0601	-0.0365	-0.0043	-0.0834	-0.0563	-0.0433	-0.0355
South Africa	-0.0286	-0.0697	-0.0612	-0.0548	-0.0581	-0.0600	-0.0175	-0.0517
Southern Africa	-0.0281	-0.0697	-0.0623	-0.0556	-0.0565	-0.0609	-0.0165	-0.0514
Tunisia	0.0214	-0.0004	0.0066	0.0146	0.0724	0.0095	0.0318	-0.0186
West Africa	-0.0070	-0.0340	-0.0095	-0.0210	-0.0372	-0.0440	-0.0196	-0.0415
BCOM	-0.0309	0.0392	0.0117	0.0049	-0.0292	-0.0377	-0.0141	-0.0205
MSCI-DW	0.0173	0.0018	0.1151	0.0302	0.0543	-0.0311	-0.0223	-0.0476
MSCI-EM	-0.0229	-0.0768	-0.0703	-0.0622	-0.0603	-0.0727	-0.0445	0.0457
	Panel B: Bilateral exchange rates expressed in US Dollars ($)							
Botswana	0.0814	-0.0189	-0.0171	0.0361	-0.0176	-0.0154	-0.0181	0.0049
Egypt	0.0220	0.1266	-0.0192	0.0149	0.0362	0.0223	0.0466	0.0481
East Africa	0.0442	-0.0284	-0.0017	0.0324	-0.0584	-0.0434	-0.0213	-0.0374
Ghana	0.0401	-0.0171	-0.0274	0.0199	0.0299	-0.0250	0.0417	0.0161
Kenya	0.0726	-0.0140	-0.0279	-0.0416	-0.0423	0.0258	0.0221	-0.0724
Morocco	0.0037	-0.0272	-0.0358	-0.0297	-0.0164	-0.0067	-0.0572	0.0048
Nigeria	0.0007	-0.0193	-0.0135	0.0171	-0.0535	-0.0540	-0.0633	-0.0198
North Africa	0.0105	-0.0498	-0.0482	-0.0267	-0.0516	-0.0147	-0.0661	-0.0087
South Africa	0.0823	-0.0173	-0.0423	-0.0173	-0.0576	-0.0745	-0.0367	-0.0532
Southern Africa	0.0840	-0.0167	-0.0425	-0.0171	-0.0562	-0.0741	-0.0372	-0.0540
Tunisia	0.0680	-0.0324	-0.0334	-0.0035	-0.0420	0.0097	-0.0075	0.0077
West Africa	0.0129	-0.0275	-0.0255	0.0231	-0.0556	-0.0598	-0.0693	-0.0221
BCOM	0.0402	0.0619	0.0547	0.0066	0.0026	-0.0393	-0.0184	-0.0384
MSCI-DW	0.0145	-0.0023	0.0994	0.0960	-0.0043	0.0036	0.0237	-0.0074
MSCI-EM	0.0357	-0.0084	-0.0378	-0.0246	-0.0539	-0.0450	-0.0192	-0.0958

The table depicts the Pearson correlation coefficients for volatilities from 3rd January, 2003 to 29th October, 2014. Volatilities are based on absolute returns.
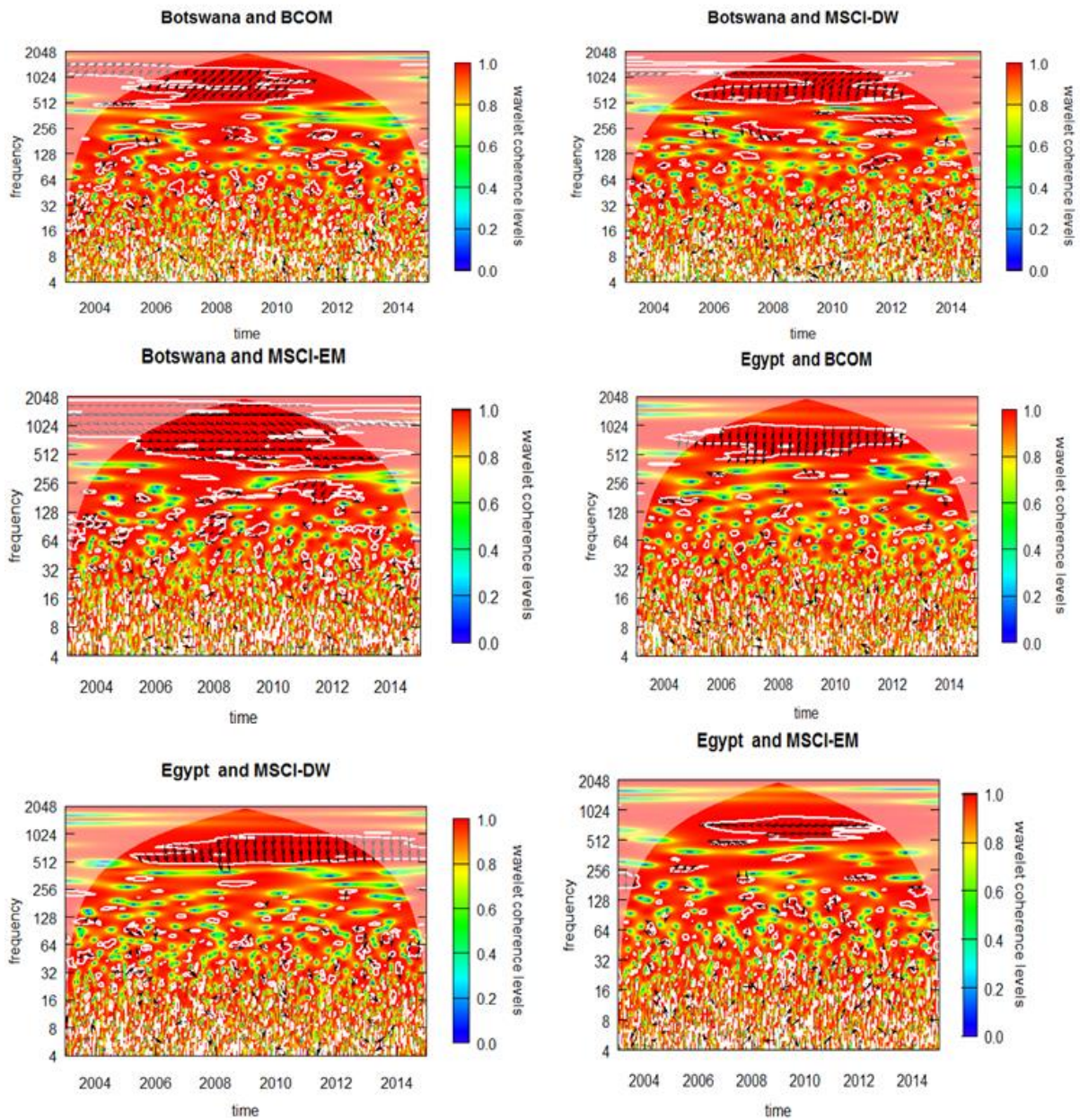
Table 3: Correlations of volatility of returns

	BCOM	Botswana	East Africa	Egypt	Ghana	Kenya	Morocco	MSCI-DW	MSCI-EM	Nigeria	North Africa	South Africa	Southern Africa	Tunisia	West Africa
BCOM															
Botswana	0.0815														
East Africa	0.0974	0.0564													
Egypt	0.0179	-0.0112	0.0105												
Ghana	-0.0008	0.3133	-0.0134	0.0215											
Kenya	0.0544	0.1498	0.0961	-0.0225	0.0156										
Morocco	-0.0031	0.0919	0.0627	-0.0267	-0.0074	0.0285									
MSCI-DW	0.0774	0.0465	0.0739	0.0131	0.0084	-0.0107	-0.0328								
MSCI-EM	0.1077	0.0877	0.1867	-0.0420	-0.0199	0.1835	0.0307	0.0390							
Nigeria	0.0547	0.0610	0.1045	0.0039	0.0189	0.0871	0.0411	0.0379	0.0792						
North Africa	-0.0017	0.0982	0.0941	-0.0330	0.0051	0.0445	0.9605	-0.0307	0.0567	0.0587					
South Africa	0.1097	0.2138	0.2240	-0.0511	-0.0053	0.1147	0.1415	0.0694	0.1861	0.0846	0.1504				
Southern Africa	0.1143	0.2217	0.2263	-0.0494	-0.0046	0.1587	0.1408	0.0716	0.1897	0.0852	0.1485	0.9988			
Tunisia	0.0921	0.1270	0.1321	-0.0066	0.0268	0.0658	0.1065	0.0032	0.0807	0.0311	0.1103	0.2461	0.2492		0.1169
West Africa	0.0596	0.1752	0.1061	0.0057	0.1692	0.0927	0.0558	0.0391	0.0887	0.9700	0.0759	0.1065	0.1077	0.0595	

The table depicts the Pearson correlation coefficients for volatilities from 3rd January, 2003 to 29th October, 2014. Volatilities are based on absolute returns.

Figure 1: Daily volatility changes in country and regional stock markets in Africa as well as global market indices
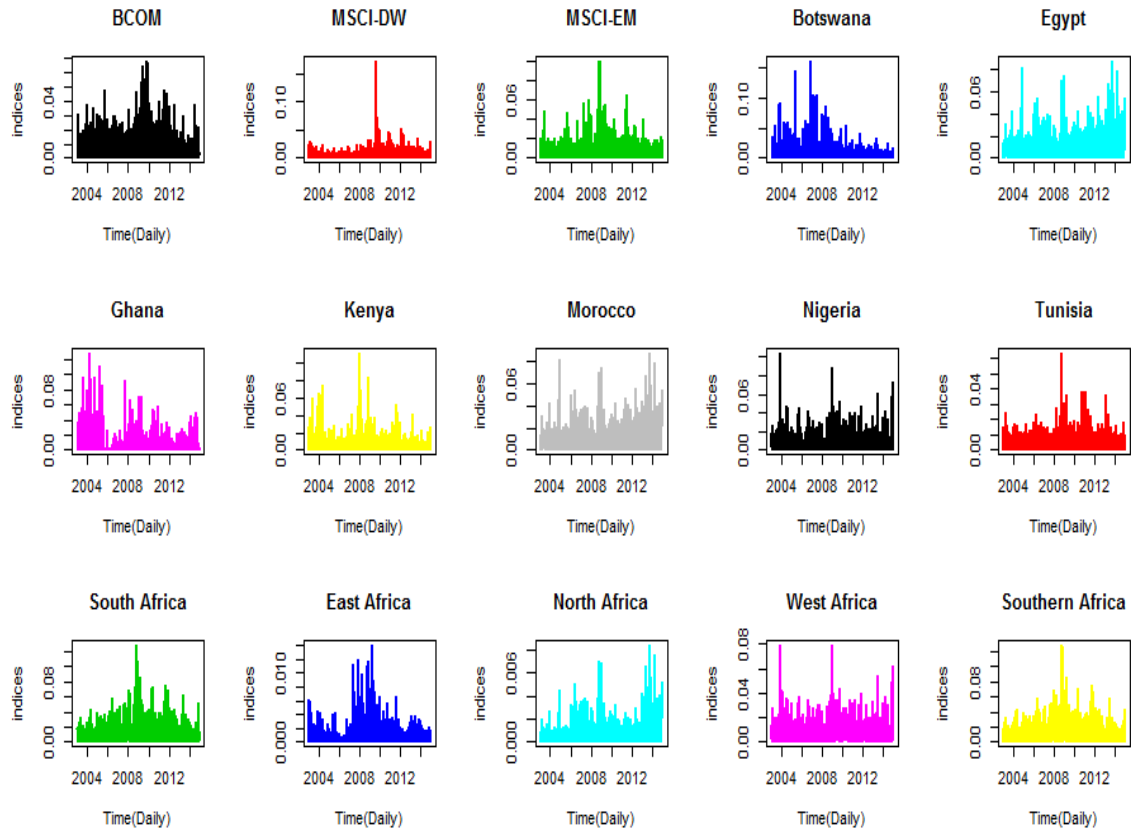
Figure 2: Detection of multiple structural shocks (changes) with BIC
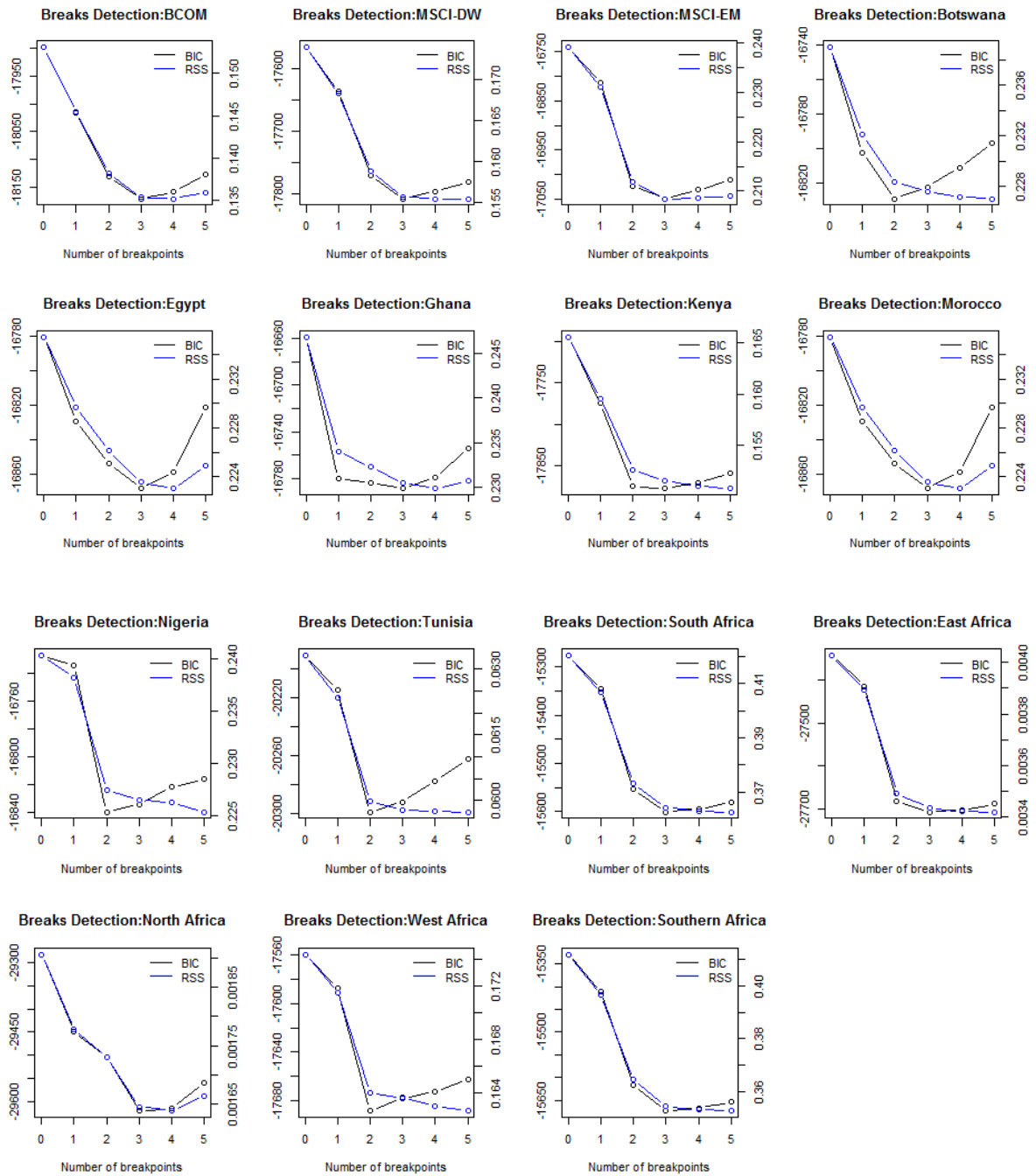
Figure 3:

This figure shows the wavelet power spectrum of the volatilities of selected individual and regional African stock markets, developed and emerging stock markets, as well as the commodities markets, from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.

East Africa Southern Africa West Africa
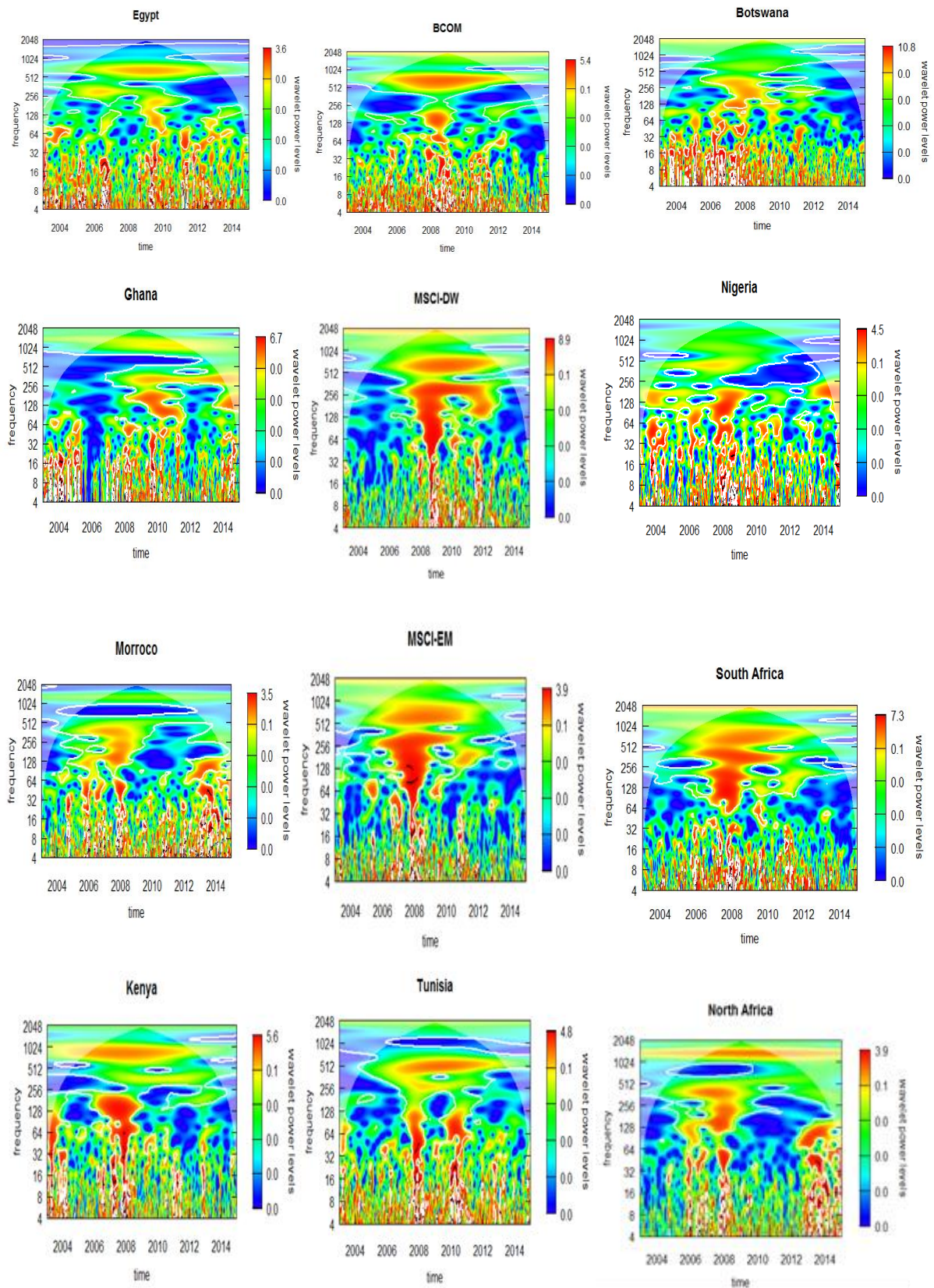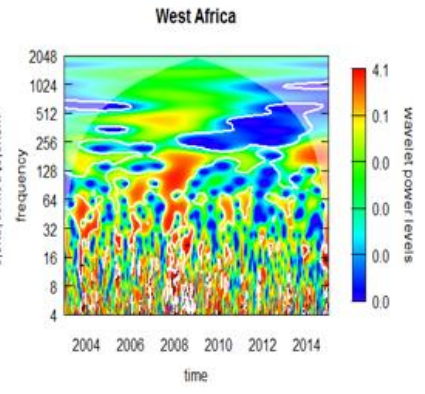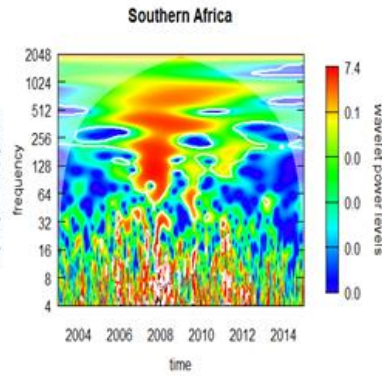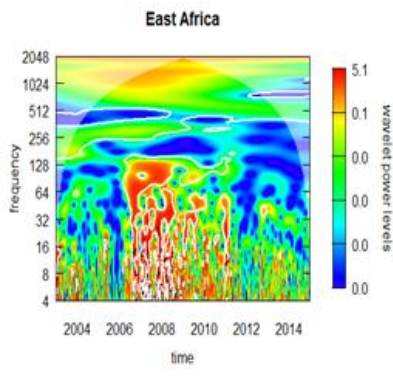
Figure 4:

This figure shows the cross-wavelet squared coherency and phase difference plots between the African stock markets volatility on one hand and those of MSCI-DW, MSCI-EM, and BCOM on the other hand from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.
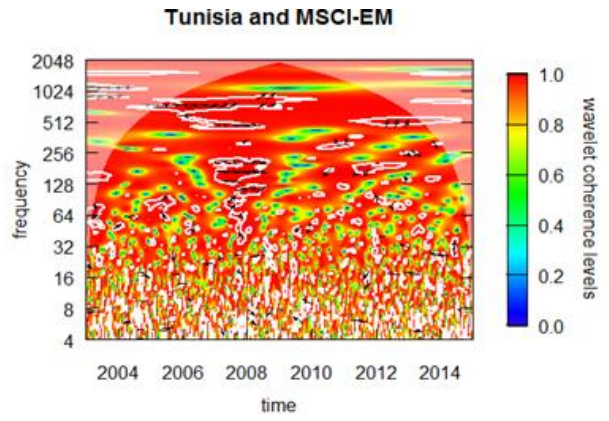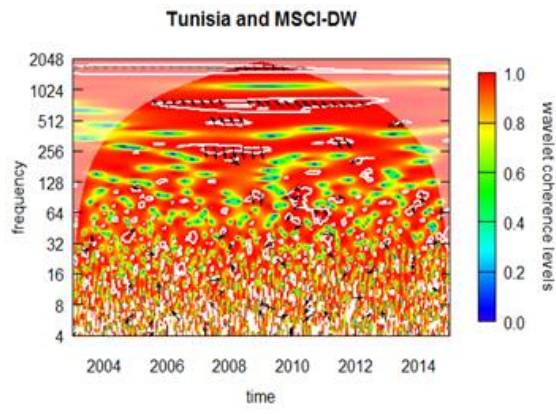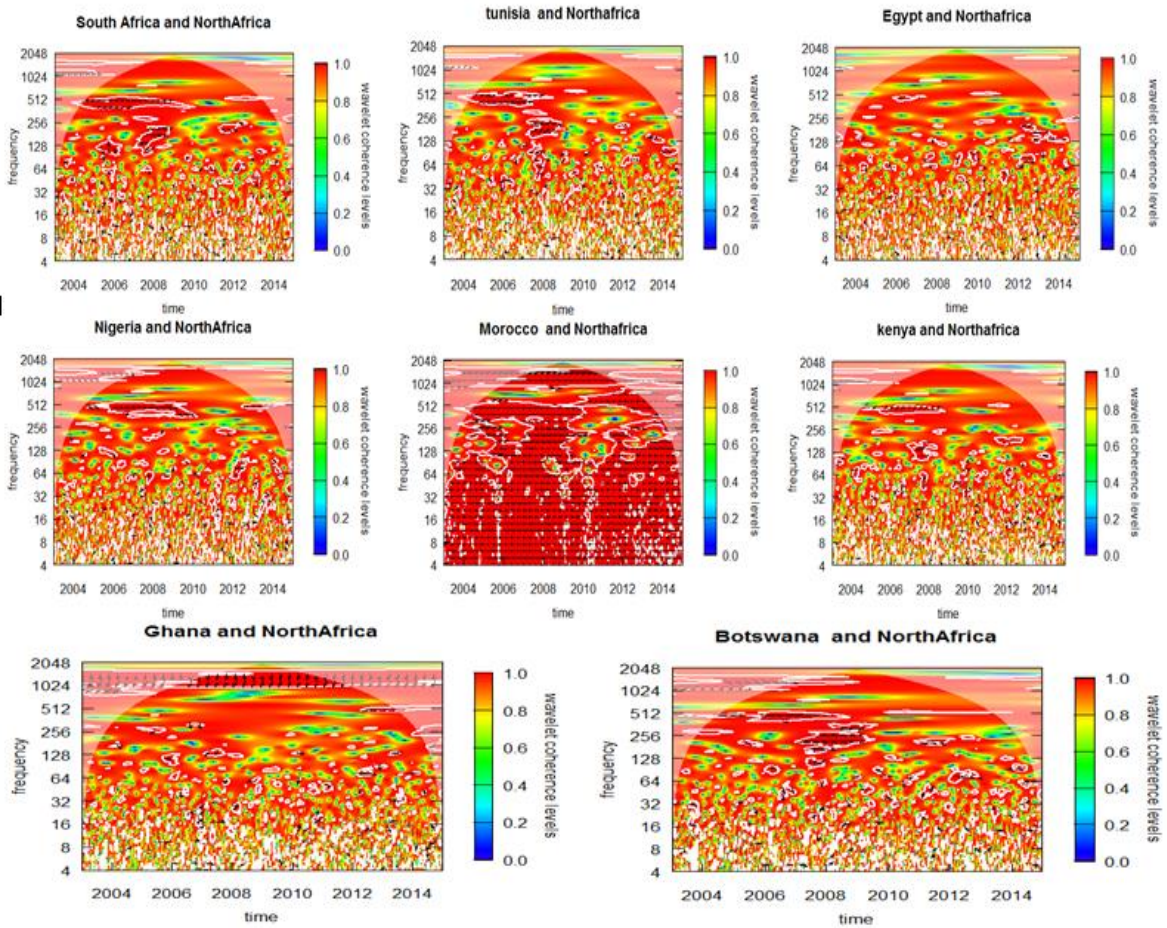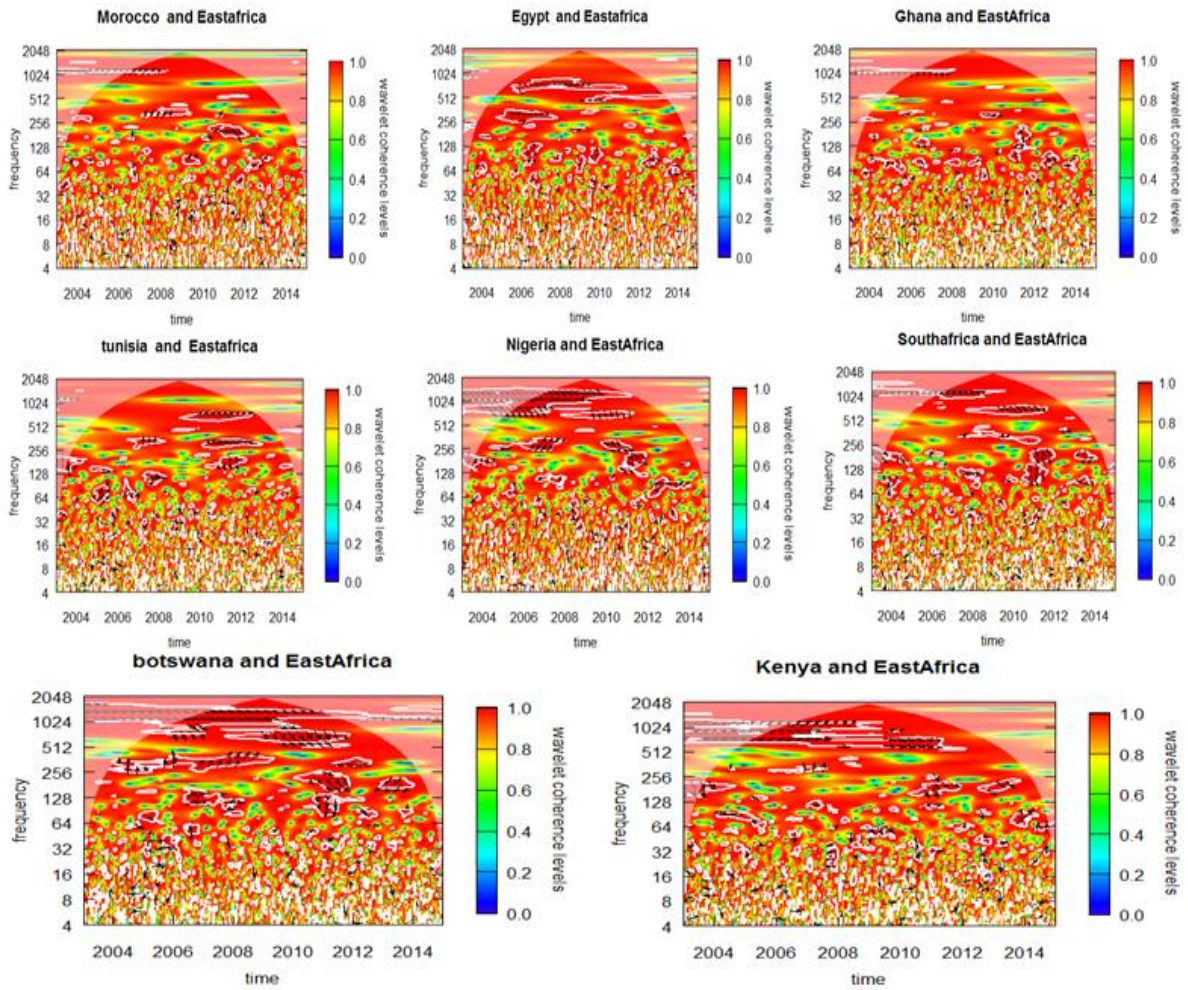
Ghana and BCOM

Ghana and MSCI-DW

Ghana and MSCI-EM

Kenya and BCOM

Kenya and MSCI-DW

Kenya and MSCI-EM

Morroco and BCOM

Morroco and MSCI-DW

Morroco and MSCI-EM

Nigeria and BCOM

Nigeria and MSCI-DW

Nigeria and MSCI-EM

South Africa and BCOM

South Africa and MSCI-DW

South Africa and MSCI-EM

Tunisia and BCOM

Tunisia and MSCI-DW

Tunisia and MSCI-EM
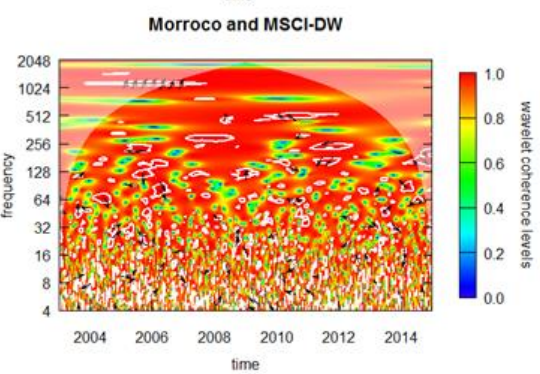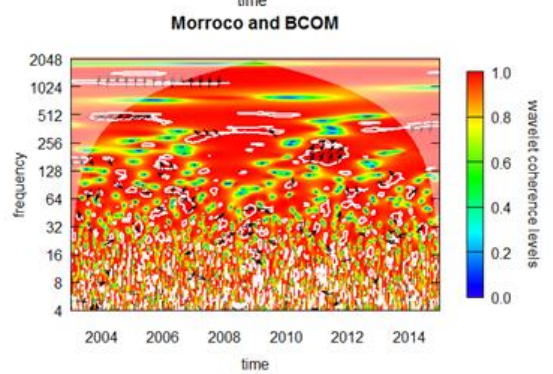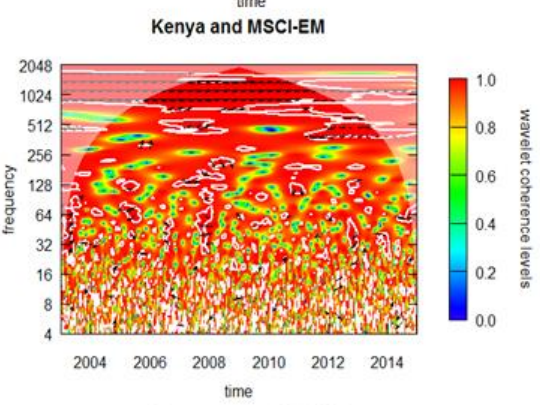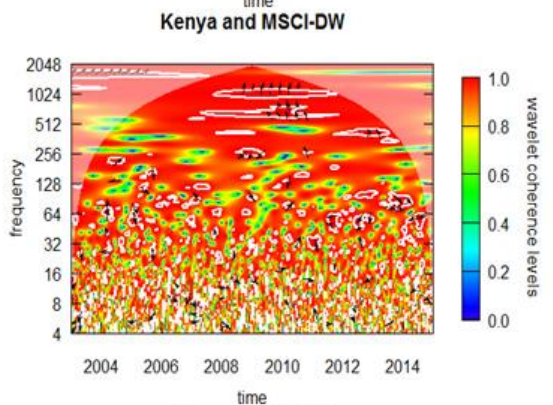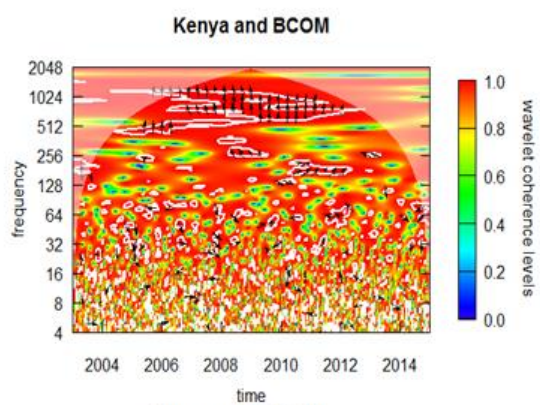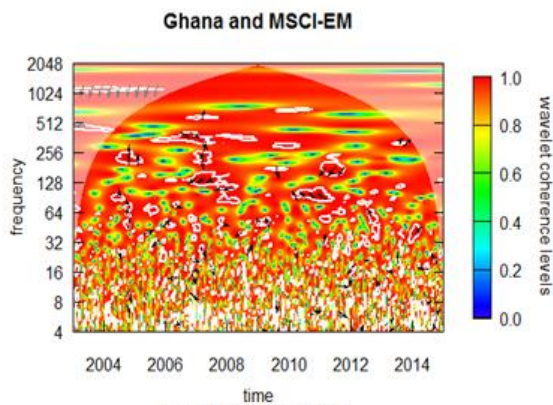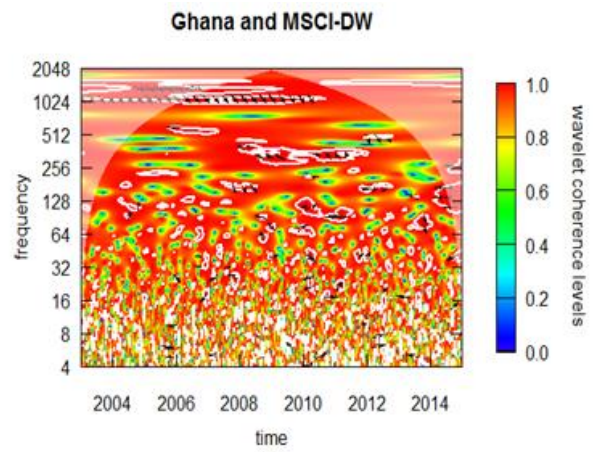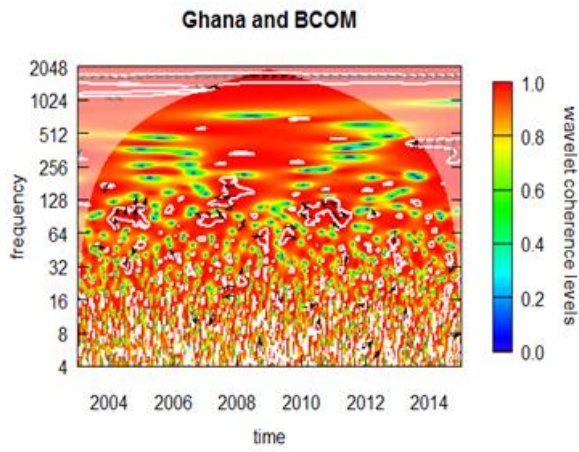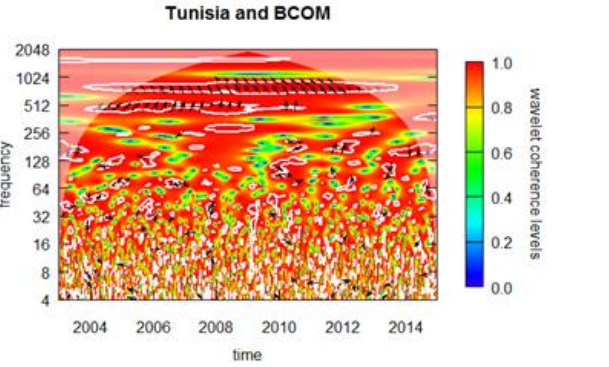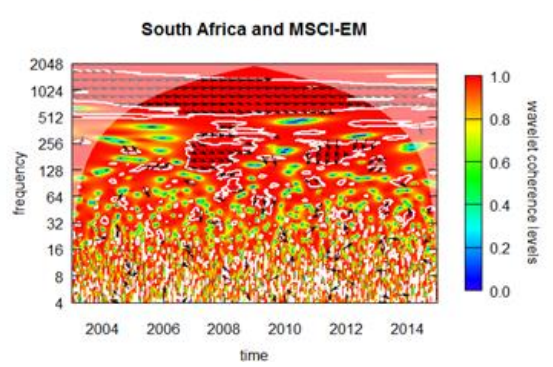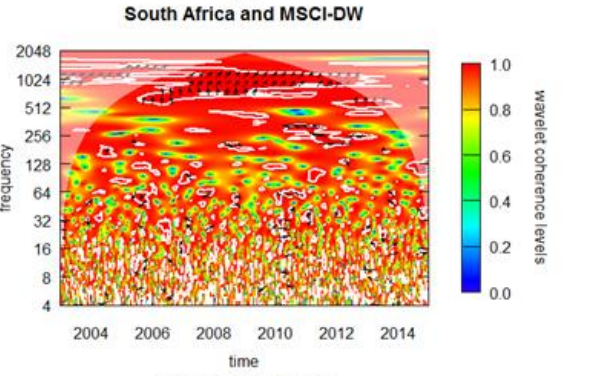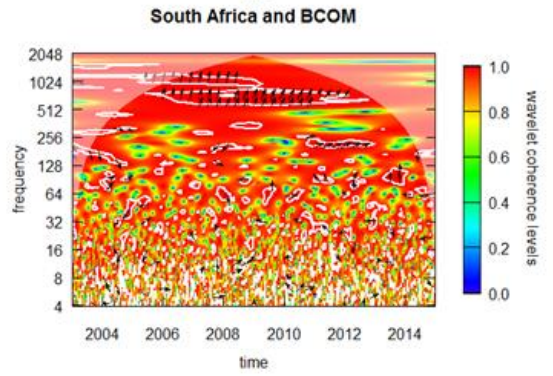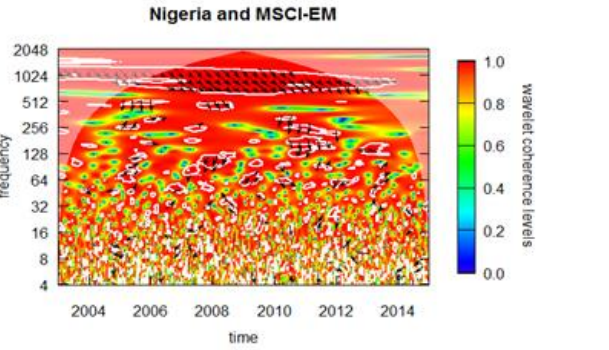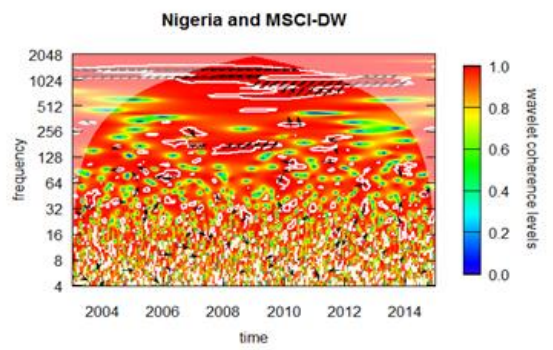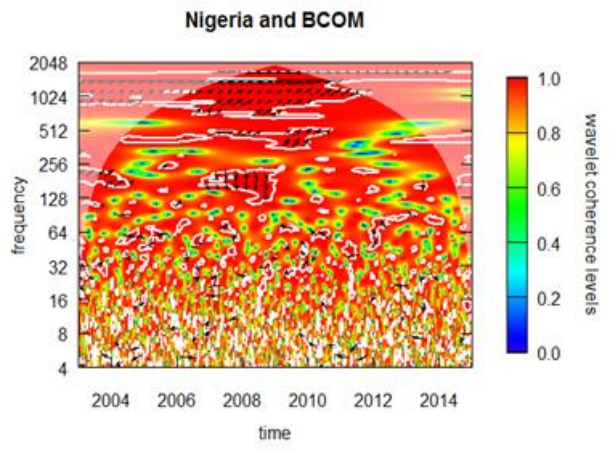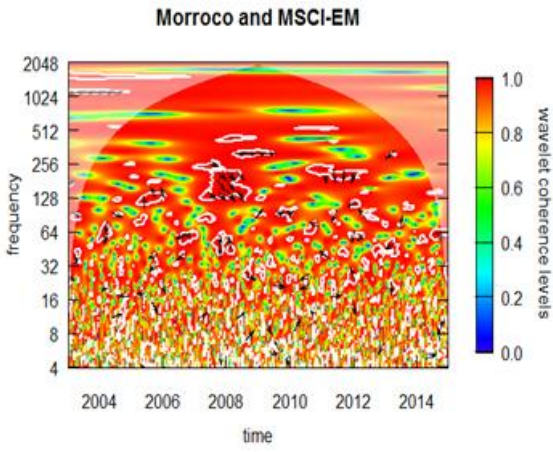
Figure 5a-5d:

This figure shows the cross-wavelet squared coherency and phase difference plots between volatilities of individual Africa's stock markets and each of the regional stock markets from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.
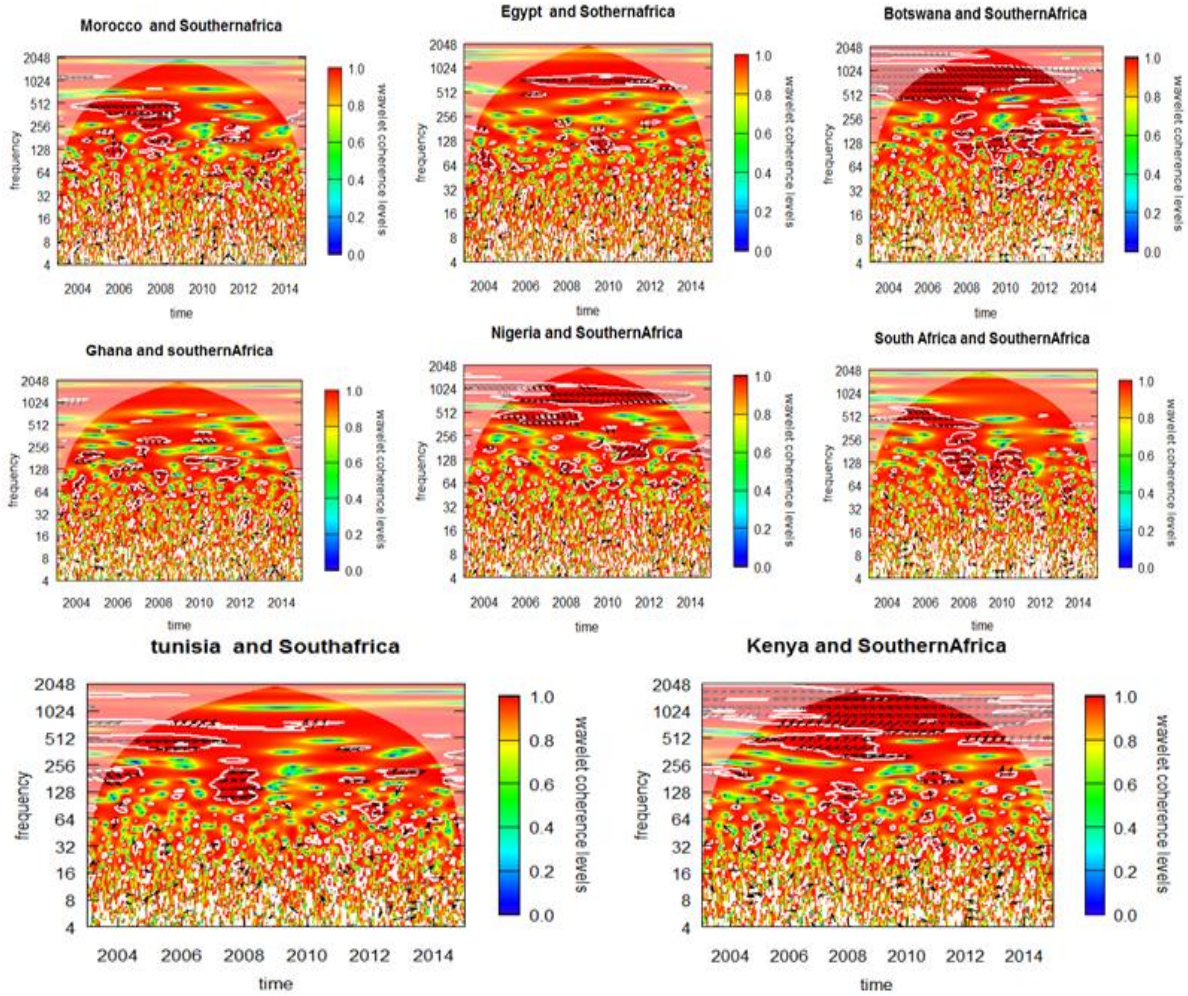
(a) Co-movement with the North African regional market

(b) Co-movement with the East African regional market

Morocco and Eastafrica

Egypt and Eastafrica

Ghana and EastAfrica

tunisia and Eastafrica

Nigeria and EastAfrica

Southafrica and EastAfrica

botswana and EastAfrica

Kenya and EastAfrica

(c) Co-movement with the Southern Africa regional market

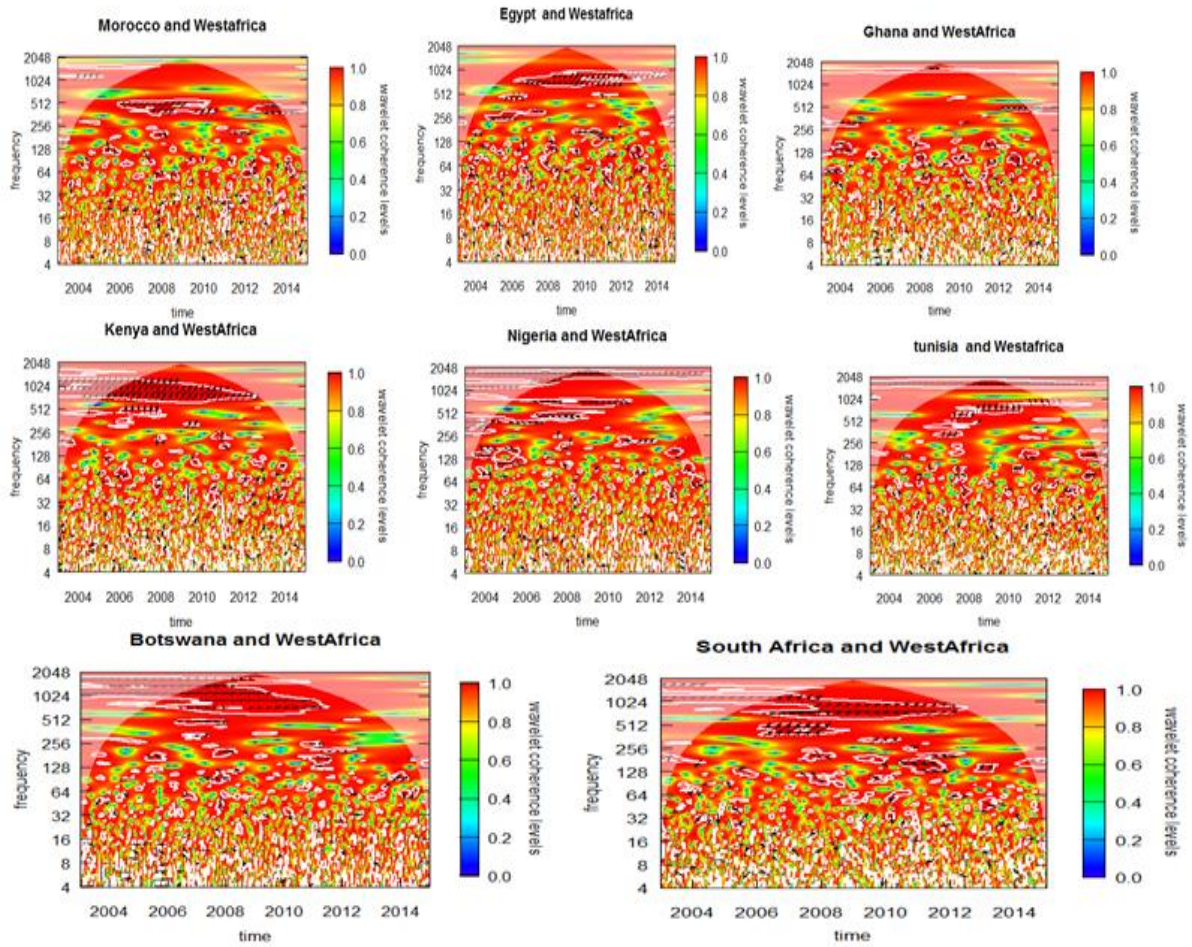**(d) Co-movement with the West African regional market**

Figure 6a-6b:

This figure shows the cross-wavelet squared coherency and phase difference plots between volatilities of Africa's stock markets on one hand, and bilateral exchange rates expressed in US dollars and Euro on the other hand from 3rd January, 2003 to 29th December, 2014. Volatilities are based on absolute returns.

(a)   Co-movement with US dollar FX
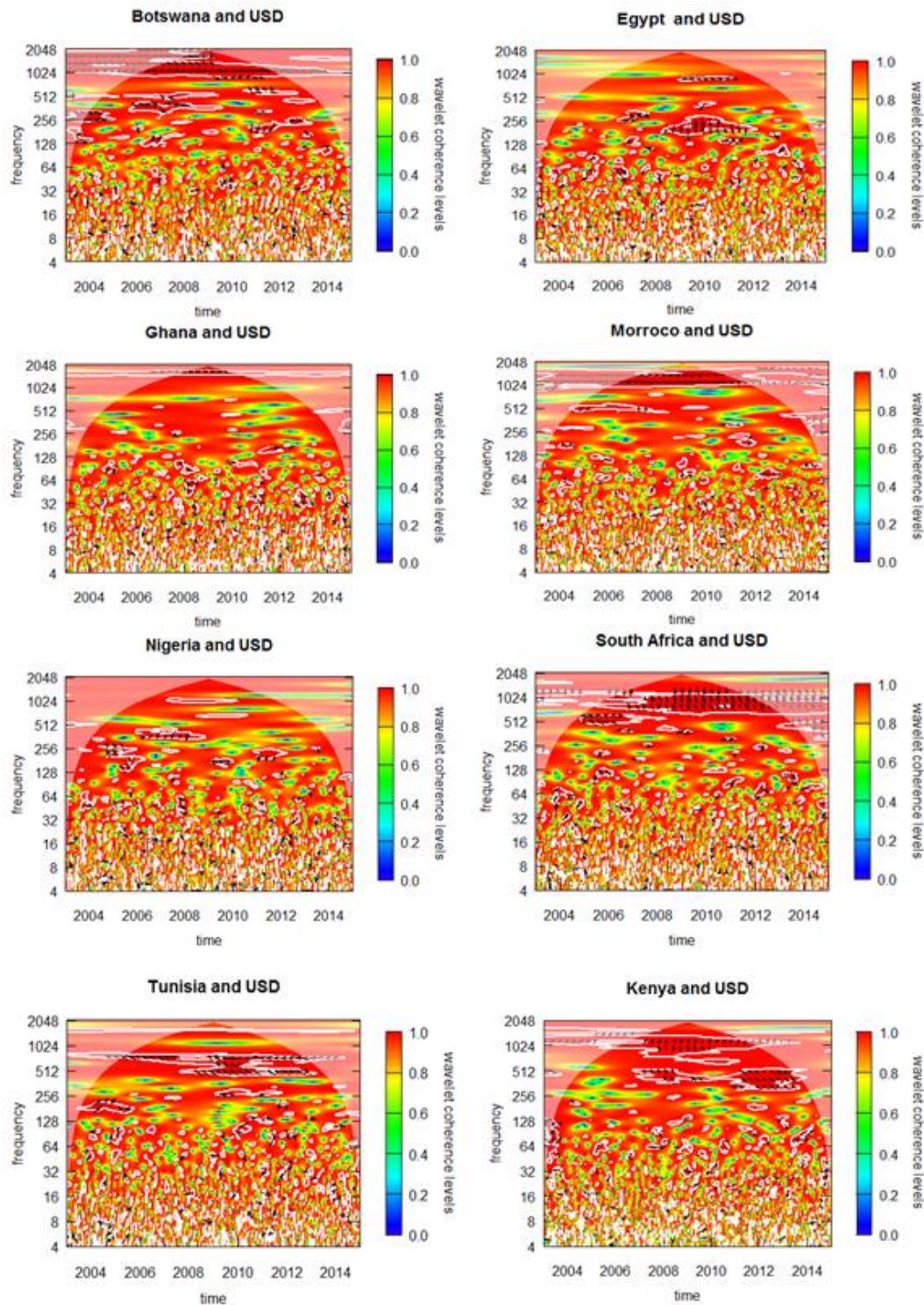
(b) Co-movement with Euro FX
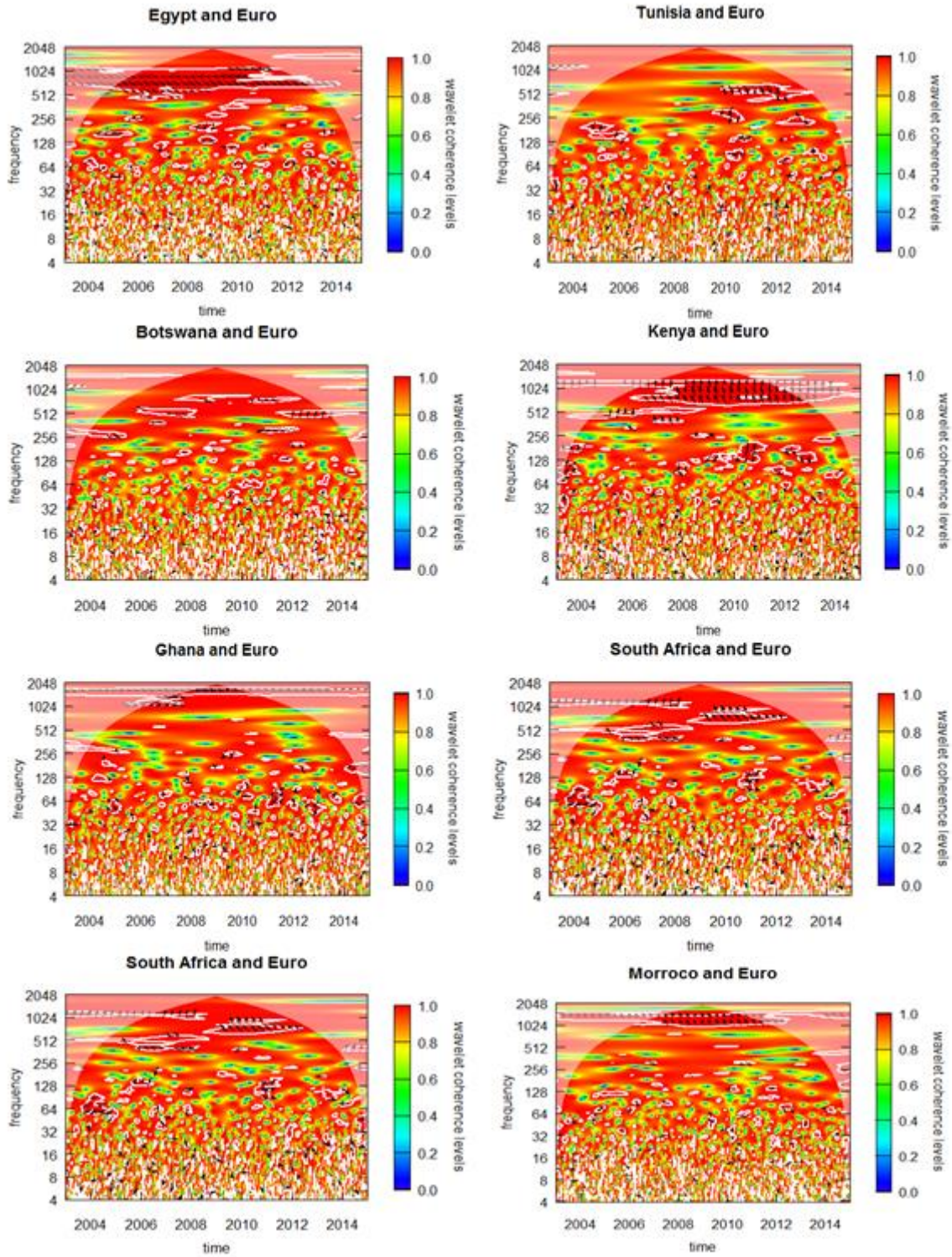
Appendix 1: **Test for multiple structural shocks (changes)**

	m – change points (*change dates*)		
	***m*=1**	***m*=2**	***m*=3**
BCOM	*1006 (08:18:08)*	*1395 (04:09:10)*	*2001 (08:16:12)*
MSCI-DW	*1009 (08:21:08)*	*1405 (04:23:10)*	*2091 (12:20:12)*
MSCI-EM	*770 (12:14:06)*	*1220 (07:30:09)*	*1922 (04:26:12)*
Botswana	*997 (07:29:08)*	*1430 (05:28:10)*	*************
Egypt	*580 (01:19:06)*	*1148(04:10:09)*	*2023 (09:17:12)*
Ghana	*1075 (12:09:08)*	*1585 (01:04:11)*	*2108 (01:21:13)*
Kenya	*855 (09:04:07)*	*1244 (09:02:09)*	*1902 (03:27:12)*
Southern Africa	*832 (07:02:07)*	*1221 (07:31:09)*	*1991 (08:02:12)*
Morocco	*574 (01:02:06)*	*1141 (04:01:09)*	*2018 (09:10:12)*
Nigeria	*963 (05:15:08)*	*1352 (02/05/10)*	*************
Tunisia	*999 (07:31:08)*	*1741 (08:12:11)*	*************
North Africa	*574 (01:02:06)*	*1141 (04:01:09)*	*2091 (12:20:12)*
East Africa	*785 (4:18:07)*	*1330 (01:06:10)*	*1792 (10:24:11)*
South Africa	*832 (07:02:07)*	*1221 (07:31:09)*	*1991 (08:02:12)*
West Africa	*968 (05:28:08)*	*1357 (02:12:10)*	*************

m–change points denote the number of detected multiple shocks (change) points; and change dates gives the dating of the change points detected. The dating for the changes is of format: (month: day: year)