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Beginning an African Stock Markets Integration? A Wavelet Analysis

Grakolet Arnold Z. Gourène*

Laboratory of Mathematics of the Decision and Numerical Analysis

Cheikh Anta Diop University

B.P. 5005 Dakar-Fann, Sénégal

Pierre Mendy†

Laboratory of Mathematics of the Decision and Numerical Analysis

Cheikh Anta Diop University

B.P. 5005 Dakar-Fann, Sénégal

Aguin Franck Yvon Elegbe‡

Ph.D Student in Economics, Cheikh Anta Diop University

B.P. 5005 Dakar-Fann, Sénégal

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Abstract

This paper examines the integration of the six largest African stock markets at different timescales. We want to see whether the numerous measures and reforms put in place to integrate the African stock markets are effective. First, we used the Wavelet Multiple Correlation and the Wavelet Multiple Cross-Correlation proposed by Fernández-Macho (2012). Then, we combine the spillovers index based on generalized vector autoregressive proposed by Diebold and Yilmaz (2012) with the Maximal Overlap Discrete Wavelet Transform. We find that after all the reforms, African stock markets integration remains weak and tends to decline despite some small progress in the flow of financial information. We also find that the integration of African stock exchanges varies according to timescales. More efficient measures are therefore needed for the effective integration of African financial markets, but also for policies that better promote exchanges between these stock markets.

JEL Classification: C4, F3, G1.

Keywords: Stock Markets Integration, Wavelet Multiple Correlation, Wavelet Multiple Cross-Correlation, Generalized VAR.

*Corresponding Author. Tel: +221774475366. Email: grakolet88@gmail.com

†Email: pierre.mendy@ucad.edu.sn

‡Email: israelelegbe7@gmail.com

1 Introduction

Over the last decades, the stock markets in Africa have experienced a certain growth. Many stock markets have emerged in various countries and some have even attracted attention because of their performance (see PwC, 2015, 2016; ASEA, 2012, 2015). The number of stock markets has increased from 12 to 25 today. The capitalization of the 10 largest African stock markets recorded exceptional growth of 390.77% from 2000 to 2010. Between the years 2007 and 2009, more than \$10bn[1] of capital were identified in 18 stock exchanges of 200 new companies IPO[2] and more recently we had 125 IPOs from 2011 to 2016 (raising \$6.1bn).

This sudden development of financial markets bodes well for African economies. Indeed, Bagehot (1873), Hicks (1969) and Schumpeter (1912) affirmed that good financial institutions positively impact productivity of capital and promoted technical innovation. Levine (1997) said that the financial market played a prominent role in growth, capital accumulation and economic development. However, this rapid growth in financial markets does not appear to be sufficient. Indeed, by 2015, African financial markets accounted for only 1.4% of the world's market capitalization[3]. These results show that African financial markets, despite their notable advances, remains lagging behind global finance.

Some authors have shown that a more integrated African financial market would be more efficient and therefore more internationally competitive. Fish and Biekpe (2002) argued that an African regional stock exchange may improve liquidity while reducing cost of operations. Irving (2005) said that an integration between African financial markets from different African economic zones allow a better depth and a wider choice of financial products. According to ARIA III (2008), market integration will lead to increase the liquidity in African financial markets. Several countries will be able to pool their resources for regional cooperation and stock markets development. For Lugangwa (2012), the cooperation and integration of African markets will make them more visible to global investors. Given their small sizes, UNCTAD (2014) suggest that African financial markets should unite on a continental or regional scale for their development.

Many reforms and measures have been taken to integrate the African stock markets between them but also with the outside. The creation of African Securities Exchanges Association (ASEA)[4] to improve the visibility of African Securities in the world, provide a better knowledge of African stock market and promote trade between African financial markets. The establishment of two regional stock exchanges, the Bourse Régionale des Valeurs Mobili'eres (BRVM) from the WAEMU[5] and the Bourse des Valeurs Mobilires de l'Afrique Centrale (BVMAC) from the CEMAC[6]. The implementation of closer cooperation and harmonization between stock markets in the same region (ECOWAS[7], AMU[8]...) In order to improve liquidity and market depth. In 2014 East African stock markets[9] have taken steps towards a harmonized capital market (see UNCTAD, 2014; PwC, 2015). The

[1] Billion
[2] Initial Public Offering
[3] With 77 % came only from the South African stock market
[4] URL:http://www.african-exchanges.org/
[5] West African Economic and Monetary Union
[6] Central African Economic and Monetary Community
[7] Economic Community of West African States
[8] Arab Maghreb Union
[9] Kenya, Uganda, Tanzania, Rwanda, Burundi

stock exchanges of WAEMU[10], Nigeria and Morocco respectively signed partnerships with Paris EUROPLACE, London Stock Exchange Group (LSEG) and FTSE Group. Since 2011, The ASEA, in partnership with the Financial Times Stock Exchange (FTSE) created two indices: the FTSE ASEA pan African Index Series and the FTSE ASEA pan Africa Index ex South Africa. One of the role of the indices is to highlight the performance of African stock markets(ASEA, 2015).

Several authors have therefore been interested in the integration of these African financial markets. Collins and Biekpe (2003a,b); Wang et al. (2003) were interested in the integration of African stock markets during and after the Asian crisis of 1997. Adjasi and Biekpe (2006); Agyei-Ampomah (2008); Boamah (2013) studied the link between African stock exchanges. Using the Diebold and Yilmaz (2012) spillovers index, Sugimoto et al. (2014); Fowowe and Shuaibu (2016) analyzed the relationship between the African stock markets during the U.S financial crisis and the European debt crisis. All these works agreed that African financial markets are poorly integrated.

However, these works have limitations in their analysis of the relationship between financial markets. The only temporal aspect is not very realistic given the nature of the financial markets. Stock markets are a complex system composed of different agents with different trading horizons that form the dynamics of the markets. The trading scale[11] is therefore a very important aspect. Consider decisions at different timescales (see Candelón et al., 2009) gives more details on the co-movement between stock markets. Methods such as co-integration and error correction model (see Engle and Granger, 1987) are then limited because they take into account only two scales (short and long run) on several. In the world markets co-movement, these methods are illustrated by works such as Fernández-Macho (2012) in Europe, Tiwari et al. (2013) in Asia, Loh (2013) between Asia and the outside, Graham and Nikkinen (2011), Graham et al. (2012, 2013), Madaleno and Pinho (2012) in emerging and developed stock markets , Aloui and Hkiri (2014) in Gulf Cooperation Council, Gallegati (2005) between MENA[12] and outside and Rua and Nunes (2009) between global financial markets.

Here we combine wavelet methods and traditional methods. Wavelets methods analyze the relationship between stock markets at several timescales (horizon or frequency). This approach provides more details and a better understanding of the relationship between financial markets that is crucial for financial institutions.

In our work, we want to see whether all the measures taken by the financial authorities tend to integrate African stock markets. This could be the cause of this financial market which continues to grow despite the various global crises. First, we use the Maximal Overlap Discrete Wavelet Transform (MODWT) on the different stock markets returns. These methods allow to data from financial markets to be available at different time scales. Then, we employ the Wavelet multiple correlation and the Wavelet multiple cross correlation proposed by Fernández-Macho (2012), to study the relationship between the African stock markets. After, we apply the Diebold and Yilmaz (2012) spillovers index to data to determine the spillovers from the African financial markets towards the African financial markets themselves at different scales. Our study period is very interesting for the analysis of the relations between financial markets. It covers the last two financial crises, U.S financial crisis

[10] West Africa Economic and Monetary Union
[11] Trading horizon
[12] Middle East and North Africa

and the European debt crisis.

The rest of the study is structured as follows. Section 2 gives a overview of the literature on stock markets integration. Section 3 details the econometric methodology used. Section 4 examines the data and the empirical results and Section 5 concludes.

2 Literature Review

Some authors have been interested in the integration of African stock markets. Collins and Biekpe (2003a) showed that the most developed African stock markets (Egypt and South Africa) suffered from contagion during the Hong Kong crisis of 1997. Collins and Biekpe (2003b) argued that the co-movement of African financial markets has declined in regional blocs. Using co-integration and error correction model Wang et al. (2003) demonstrated that integration between African stock markets varied over time and appeared to decline after the Asian crisis of 1997. Adjasi and Biekpe (2006) has found a unique long-term relationship between African stock markets and a short-term dynamic of African stock markets returns that affect the South African and Ghanaian stock exchanges. Using the measurement's method of the score market integration proposed by Barari (2004), Agyei-Ampomah (2008) found a low level of correlation between the African stock markets. Recently Boamah (2013) through a multi-factor pricing model, showed that the integration of the African stock markets evolved over time. Using the Diebold and Yilmaz spillovers index, Sugimoto et al. (2014); Fowowe and Shuaibu (2016) concluded that the spillovers between African financial markets are very weak. Regarding the wavelet literature on the integration of financial markets, it is relatively recent at the world level. At the African level, the literature is practically non-existent. We can cite works such as Gallegati (2005) which showed that the MENA stock markets are neither regionally nor internationally integrated. Rua and Nunes (2009) found that the Japanese stock market was poorly integrated with the other developed financial markets[13]. The relationship between these stock markets varied with timescales. Graham and Nikkinen (2011) demonstrated that the co-movement between Finland and the emerging stock markets was reduced to long-term fluctuations. With regard to the co-movement with the stock markets of the developed regions[15], it was present in all frequencies, with strong co-movements at high frequencies. Graham et al. (2012) found a strong co-movement between stock markets that differs from one country to another. According to the authors, the U.S stock market is highly correlated to the stock markets of Brazil, Mexico and Korea, but has a weak co-movement with the Egyptian and Moroccan stock markets. During the U.S financial crisis, the movement between stock markets increased at smaller scales. Graham et al. (2013) found a low co-movement at small scales but strong at large scales between the MENA and U.S stock markets. On the other hand, Fernández-Macho (2012) proposed two new wavelet methods: the Wavelet Multiple Correlation and the Wavelet Multiple Cross-Correlation. He applied these methods to the analysis of the co-movement of the European stock markets. The Wavelet multiple correlation emphasized a strong correlation between eurozone stock markets that is almost perfect in the long run. The author also showed small inconsistencies between the euro stock markets in the short and medium term which

[13]Germany, U.K[14] and U.S

[15]Europe, Pacific and North America

must be the result of the interaction of different agents with different decision-making horizons on the stock markets. The wavelet multiple cross-correlation method revealed that the CAC40 tends to statistically lead the rest of the euro's financial markets in the short and medium term (from one week to one month). Madaleno and Pinho (2012) demonstrated that the strength or weakness of co-movement between financial markets depends on timescales. Recently, using the methods proposed by Fernández-Macho (2012), Tiwari et al. (2013) have shown that Asian stock markets are strongly integrated at low frequencies but less integrated at high frequencies. Loh (2013) found the presence of a correlation between the Asia-Pacific stock markets and European and American stock markets. The author noted that the co-movement between the financial markets had increased during U.S financial crisis. Aloui and Hkiri (2014) showed frequent changes in the co-movement of the GCC [16] stock markets especially after the beginning U.S financial crisis at relatively high frequencies. The authors have found increased dependency between the GCC stock markets in times of financial crisis.

3 Econometric Methodology

In this section, we present the econometric methodology used to study the relationship between stock markets. First, we provide an overview of Maximum Overlap Discrete Wavelet Transform. Then, we present the Wavelet multiple correlation and the Multiple correlation Wavelet proposed by Fernández-Macho (2012). Finally, we describe the Diebold-Yilmaz spillovers index method proposed by Diebold and Yilmaz (2012).

3.1 Maximum Overlap Discrete Wavelet Transform (MODWT)

We use the MODWT to implement the stock market returns at different time scales (see Percival and Walden, 2000). The MODWT localizes variations in the signal or time series in time and frequency simultaneously. The variability and the evolution over time can be captured by decomposing the time series at many timescales.

Let X_t, the stock markets returns. The time series can be decomposed by a sequence of projections onto wavelet basis:

$$s_{J,k} = \int X_t \Phi_{J,k}(t)dt \tag{1}$$

$$d_{j,k} = \int X_t \psi_{j,k}(t)dt \tag{2}$$

where $j = 1, 2 \dots J$, the level of multiresolution and $J = log2(T)$; Φ, the father wavelet and Ψ, the mother wavelet. $s_{J,k}$, the smooth wavelet coefficient (long run movements) provides a smooth or overall pattern of the original signal and $d_{j,k}$, the detailed wavelet coefficients (short run movements) capture local fluctuations in each scale over the entire period of time series. $\Phi_{J,k}$ and $\Psi_{j,k}$ are the scaling and translation obtained from Φ and Ψ and are defined as following.

$$\Phi_{J,k}(t) = 2^{-j/2}\Phi(2^{-j}t - k) = 2^{-j/2}\Phi(\frac{t - 2^j k}{2^j}) \tag{3}$$

[16] Gulf Cooperation Council

$$\Psi_{J,k}(t) = 2^{-j/2}\Psi(2^{-j}t-k) = 2^{-j/2}\Psi(\frac{t-2^jk}{2^j}) \tag{4}$$

For the decomposition, we use Daubechies Least Asymmetric (LA) wavelet filter of length 8 because it is one of the best and most used in wavelets theory (see Percival and Walden, 2000).

The decomposition of the series by the MODWT is usually implemented by the Pyramidal Algorithm (see Mallat, 1999). The multiresolution analysis of the stock markets returns X_t using the MODWT can be written as follows.

$$X_t = \sum_{j=1}^{J} d_{j,k} + s_{J,k}, \tag{5}$$

3.2 Wavelet Multiple Correlation (WMC) and Wavelet Multiple Cross-Correlation (WMCC)

Let X_t, a multivariate stochastic process with $X_t = (x_{1t}, x_{2t}, \ldots, x_{nt})$ and $W_{jt} = (w_{1jt}, w_{2jt}, \ldots, w_{njt})$ their respective wavelet coefficients calculated by MODWT at each scale λ_j for each x_{it} process. The Wavelet Multiple Correlation (WMC)$\varphi_X(\lambda_j)$ can be described like one single set of multiscales correlations and can be calculated from X_t as follows. The square root of the regression coefficient of determination corresponding at each scale λ_j, is calculated in the linear combination of variables $\{w_{ijt}, i = 1\ldots, n\}$, whose coefficient of determination is a maximum. The coefficient of determination corresponding to the regression of a variable z_i on a set of regressors $(Z_k, k \neq i)$, can be obtained by $R^2 = \frac{1-1}{p^{ii}}$ where p^{ii} is the i_{th} diagonal element of the inverse of the correlation matrix P.

The Wavelet Multiple Correlation (WMC)$\varphi_X(\lambda_j)$ is calculated as follows.

$$\varphi_X(\lambda_j) = \sqrt{1 - \frac{1}{\text{maxdiag} P_j^{-1}}}, \tag{6}$$

where P_j correspond to the $n \times n$ correlation matrix of W_{jt} and the maxdiag (.) operator permits to select the largest element in the diagonal of the argument. In the regression of z_i on the rest of variables in the system, the R_i^2 coefficient can be equal to the square of correlation between the observed values of z_i and the fitted values $\hat{z}_i$ obtained from this regression.

The (WMC)$\varphi_X(\lambda_j)$ is also described as follows.

$$\varphi_X(\lambda_j) = Corr(w_{ijt}, \hat{w}_{ijt}) = \frac{Cov(w_{ijt}, \hat{w}_{ijt})}{\sqrt{Var(w_{ijt})Var(\hat{w}_{ijt})}}, \tag{7}$$

where the wavelet variances and covariance are given by

$$Cov(w_{ijt}, \hat{w}_{ijt}) = \bar{\gamma}_j = \frac{1}{T_j} \sum_{t=L_j^{-1}}^{T-1} w_{ijt}\hat{w}_{ijt}, \tag{8}$$

$$Var(w_{ijt}) = \bar{\delta}_j^2 = \frac{1}{T_j} \sum_{t=:j^{-1}}^{T-1} w_{ijt}^2, \tag{9}$$

$$Var(\hat{w}_{ijt}) = \bar{\xi}_j^2 = \frac{1}{T_j} \sum_{t=:j^{-1}}^{T-1} \hat{w}_{ijt}^2. \tag{10}$$

Here, w_{ij} on the set of regressors $\{w_{kj}, k \neq i\}$ leads to maximize the coefficient of determination $\varphi_X(\lambda_j)$, $\hat{w}_{ij}$ is the fitted values of regression. The number of wavelet coefficients affected by the boundary associated with a wavelet filter of length L and scale λ_j is determined by $L_j = (2^j - 1)(L - 1) + 1$, then $\tilde{T} = T - L_j + 1$ is the number of coefficients unaffected by the boundary conditions.

Lastly, allowing a lag τ between observed and fitted values of the variable selected as the criterion variable at each scale λ_j, we may also define the Wavelet Multiple Cross-Correlation (WMCC).

$$\varphi_{X,\tau}(\lambda_j) = Corr(w_{ijt}, \hat{w}_{ijt+\tau}) = \frac{Cov(w_{ijt}, \hat{w}_{ijt+\tau})}{\sqrt{Var(w_{ijt})Var(\hat{w}_{ijt+\tau})}}.$$

The construction of confidence intervals supposes that $X = (X_1 \dots X_T)$ is a realization of multivariate Gaussian stochastic process of (6) and $\tilde{W}_j = \tilde{W}_{j0} \dots \tilde{W}_{j,T-1} = \{(\tilde{w}_{1j0} \dots \tilde{w}_{njo}), \dots, (\tilde{w}_{1j,T/2^j-1})\}, j = 1 \dots J$, vectors of the wavelet coefficients obtained by MODWT at J order to each univariate time series $(x_{i1} \dots x_{iT})$ for $i = 1 \dots n$.

If $\hat{\varphi}_{X,\tau}(\lambda_j)$ is the sample wavelet correlation obtained from (6) then

$$\tilde{Z}_j \sim^a FN(z_j, (\tfrac{T}{2^j} - 3)^{-1}).$$

Here $\tilde{Z}_j = \text{arctan}h(\hat{\varphi}_{X,\tau}(\lambda_j))$ and FN stands for folded normal distribution.

The confidence interval (CI) for the sample of wavelet correlation coefficient is given as follows.

$$CI_{1-\alpha}(\varphi_{X,\tau}(\lambda_j)) = \tanh[\tilde{z}_j \pm \phi_{1-\alpha/2}^{-1} / \sqrt{T/2^j - 3}] \tag{11}$$

3.3 Diebold-Yilmaz spillover index method

We apply the method proposed by Diebold and Yilmaz (2012) to the wavelets coefficients obtained at different timescales. This method analyzes the spillovers from African stock markets toward African stock markets over many timescales.

The Diebold and Yilmaz (2012) spillover index method is an update of the previous method proposed by Diebold and Yielmaz (2009). Here, the directional spillovers is measured in a generalized VAR framework that eliminates the possible dependence of the results to the order of variables.

Assume a covariance stationary of N-variable VAR(p).

$$X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \epsilon_t, \tag{12}$$

where $\epsilon \sim (0, \Sigma)$ and ϵ is an i.i.d disturbances vector.

The moving average representation can be written as follows, $X_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}$, where A_i is an $N \times N$ coefficients matrix defines as follows, $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$ with A_i, an identity matrix and $A_i = 0$ for $i < 0$.

The moving average coefficient allows a better understanding of the method. It is based on the decomposition of the variance for analyzing forecast error variance of each variable over the entire period of the study. The variance decomposition gives access to the fraction of the H-step ahead error variance in forecasting x_i that is due to shocks to x_j, $i \neq j$ for each i.

Usually VAR innovations are simultaneously correlated while the calculation of the variance decompositions requires orthogonal innovations. The Diebold and Yielmaz (2009) method based on the Cholesky factorization depended on the order of variables. The new method use the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), which are invariant to the order of the variables. The H-step ahead forecast error variance decomposition for $H = 1, 2, \ldots,$ that uses the generalized impulse responses is defined as follows.

$$\Theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i^{'} A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} e_i^{'} A_h \Sigma A_h^{'} \Sigma e_i}, \tag{13}$$

where $i = j$, for own variance shares, $i \neq j$ for cross variance shares or spillovers with x_i and x_j, $i, j = 1, 2, \ldots N$. Σ is the variance matrix for the error vector ϵ, Θ_{ij} the standard deviation of the error run for the j^{th} equation, and e_i the selection vector with one as the i^{th} element and zeros elsewhere.

To normalize the sum of the elements in each row equal to 1 to have the information available in the variance decomposition matrix in the spillover index calculation, own variance and cross-variance shares or spillovers are defined as follows.

$$\tilde{\Theta}_{ij}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \Theta_{ij}^{g}(H)}. \tag{14}$$

We can calculate the spillovers index using the variances obtained.

$$S^{g}(H) = \frac{\sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} \tilde{\Theta}_{ij}^{g}(H)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{\Theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} \tilde{\Theta}_{ij}^{g}(H)}{N} \times 100. \tag{15}$$

The problem of variance decompositions invariant to the variables order being set, we use standardized elements of the generalized decomposition variance matrix to calculate the directional spillovers from one market (i) to others and from all other markets to one market (j).

$$S_{i}^{g}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\Theta}_{ij}^{g}(H)}{N} \times 100 \tag{16}$$

$$S_{j}^{g}(H) = \frac{\sum_{i=1, i \neq j}^{N} \tilde{\Theta}_{ij}^{g}(H)}{N} \times 100. \tag{17}$$

4 Data and Empirical Results

The data are composed of the main indices of the six largest African stock markets in terms of capitalization, South Africa (TOP40), Egypt (EGX30), Morocco (MADEX), Nigeria (NGSE), Kenya (NSE20) and West Africa Economic and Monetary Union[17] (BRVM10). We use daily data. The data sample covers the period from 6 January 2003 to 17 August 2016 (2579 observations). We note the presence of missing data due to the lack of data available at certain times and the difference in working days between the different stock exchanges. The data were obtained from the Bloomberg database. The stock market returns were calculated as follows.

$R_t = LN(P_t/P_{t-1})$,

where R are the returns and P the closing prices.

Tab. 1: Descriptive Statistics of stock markets returns.

	TOP40	EGX30	MADEX	NGSE	NSE20	BRVM10
Mean	0.0002797	0.0004736	0.0002013	1.347e-04	1.480e-04	0.0001821
Median	0.0005191	0.0008415	0.0001117	-2.100e-07	2.787e-05	0.0000000
Maximum	0.0502502	0.1174578	0.0255168	5.107e-02	5.328e-02	0.0473816
Minimum	-0.0481226	-0.0873046	-0.0358855	-4.752e-02	-6.675e-02	-0.0479173
Standard Deviation	0.006733664	0.009567575	0.004355427	0.006130683	0.005325683	0.005125892
Skewness	-0.1392378	-0.148027	-0.1447196	0.2234594	0.4868636	0.4788665
Kurtosis	8.408323	20.19298	11.41094	13.91333	32.35976	17.28368
Jarque-Bera	3151.5	31774	7611	12820	92730	22023
	(2.2e-16)	(2.2e-16)	(2.2e-16)	(2.2e-16)	(2.2e-16)	(2.2e-16)

Several summary statistics of returns are reported in Tab. 1. All stock returns have a positive mean. The African financial markets are profitable and generate profits. The largest standard deviation of EGX30 (Egypt) means that is the most volatile stock market of the panel. The MADEX (Morocco) which has the lowest standard deviation is the least volatile stock market. The analysis of skewness show a negative value[18] for the half of all stock returns. These results indicate that there is more negative returns in these series than positive returns. The high coefficient of kurtosis reveals that the returns distributions have thicker than normal Gaussian distribution tails. The Jarque-Bera normality test confirms the skewness and kurtosis results with a $pvalue < 0.05$ for all the returns.

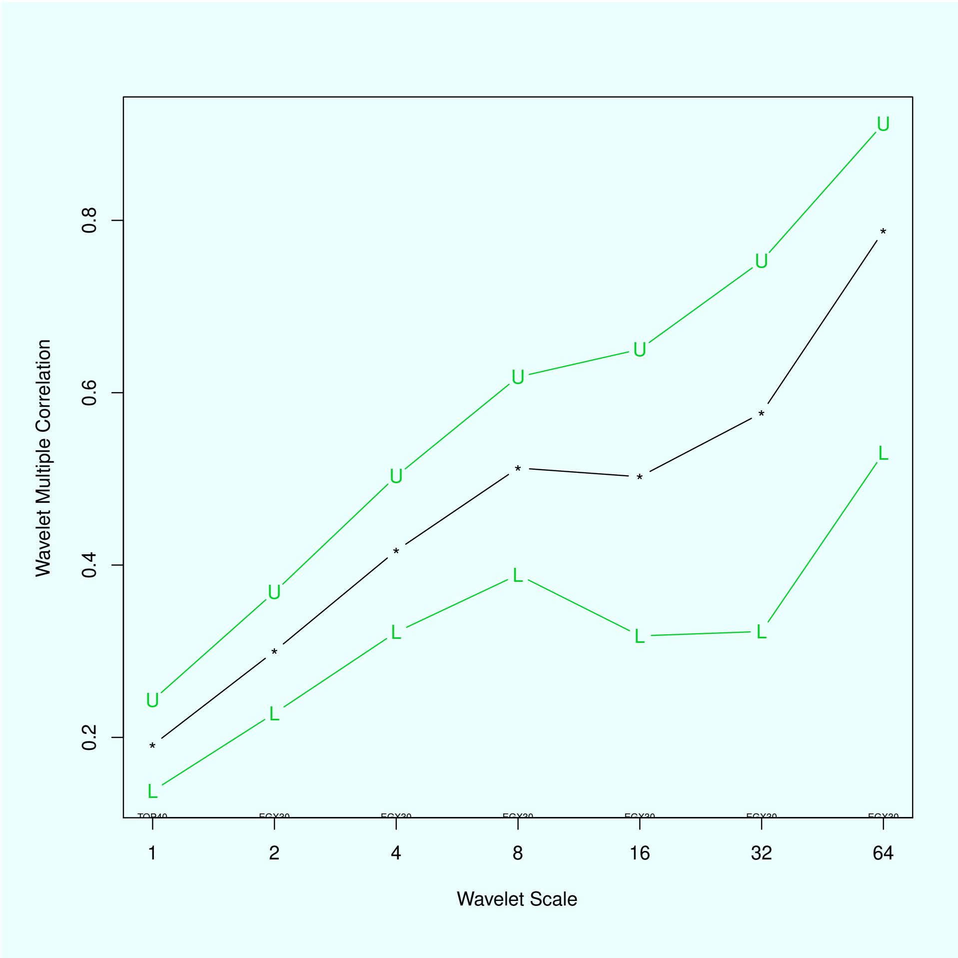
We compute the wavelet coefficients using the MODWT[19]. For the decomposition, we use Daubechies Least Asymmetric (LA) wavelet filter of length 8[20] (Percival and Walden, 2000). The maximum scales number of decomposition allowed is $log_2(N)$[21] where N is the number of observations. However, the wavelet coefficients become too small for large scales, then we decided to stop to 7 decompositions[22] or scales (Tab. 2) with 7 wavelet details[23] and 1 smooth wavelet coefficient[24] (long run dynamic). Finally we apply the Wavelet Multiple Correlation and the Wavelet Multiple Cross-Correlation to data.

[17] WAEMU.
[18] The thickest portion of their distributions is to the left
[19] Maximum Overlap Discrete Wavelet Transform.
[20] One of the best and most used in wavelets theory
[21] $log_2(2579) = 11.3$
[22] $J = 7$
[23] $D_1, \ldots, D_7$
[24] S_7

Tab. 2: Wavelet Multiple Correlation analysis.

Wavelet Scales	Time Interpretation	Correlation	Time period
D_1	2-4 days	0.1908947	intra-week
D_2	4-8 days	0.2999170	Week
D_3	8-16 days	0.4167256	Fortnightly
D_4	16-32 days	0.5126099	Monthly
D_5	32-64 days	0.5024404	Monthly to Quarterly
D_6	64-128 days	0.5764255	Quarterly to bi-annual
D_7	128-256 days	0.7877481	Bi-annual

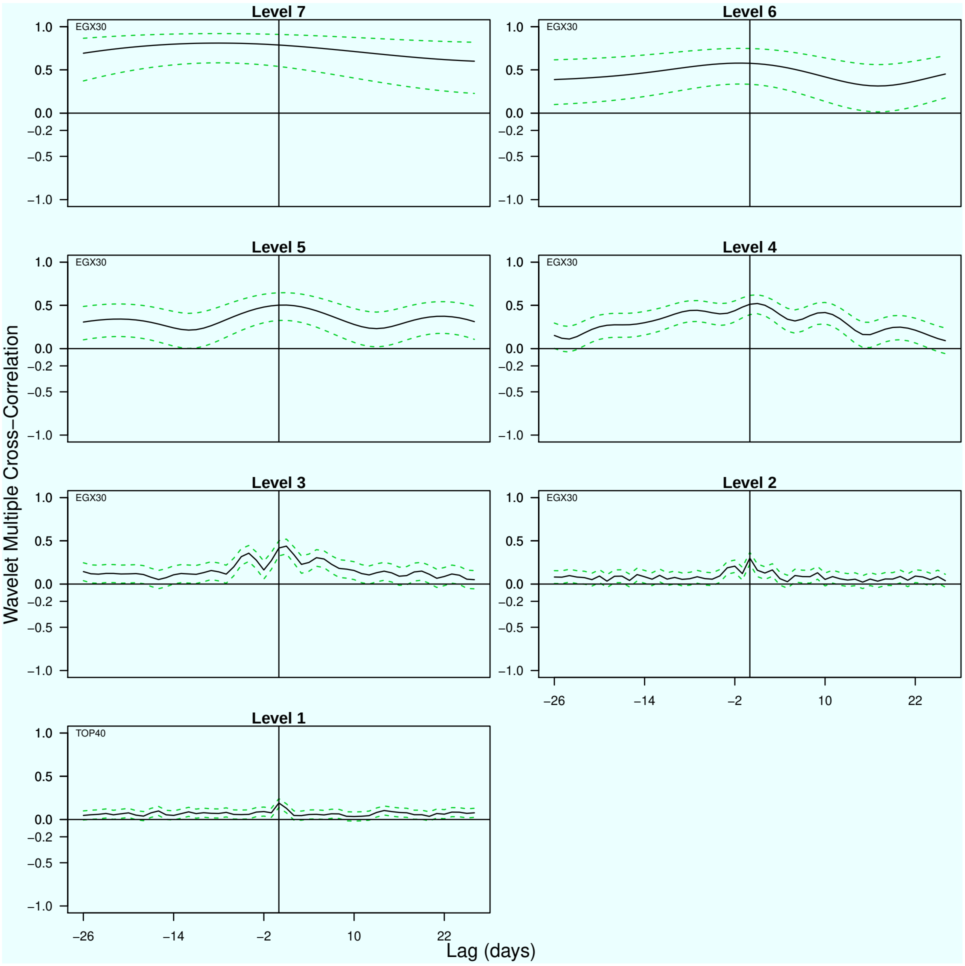
Fig. 1: Wavelet Multiple Correlation of the six major African stock markets returns.



The lines correspond to the Upper (U) and Lower (L) bounds of the 95% confidence interval.

Fig. 1 and Tab. 2 show the wavelet multiple correlation results. We remark that the correlations are very weak at small scales and tend to grow at larges scales. For the intra-week scale, the correlation is 0.19, for weekly, it is 0.29, for fortnightly, it is 0.41 and reaches until 0.78 at bi-annual scale. At the bi-annual scale (scale 7), the returns obtained in any stock markets can not be totally determined by overall performance in other markets, but are quite close.We can assume that at very large scales, African financial markets are integrated. The discrepancies between the African stock markets are very high but tend to dissipate in horizons close to one year. We note a temporary decrease in the dynamic of correlation growth at one month to one quarter scales. Fig. 2 shows the wavelet multiple cross-correlations for the different timescales with leads and lags up (26 trading days). The name of the country whose stock market maximizes the multiple correlation against a linear combination of the rest of variables is in upper-left. This stock exchange can be a potential leader or follower for the others stock markets. In our case, across all scales, the EGX30 (Egypt) is a potential leader or follower except at scale 1 where it is the TOP40 (South Africa). The results from the wavelet multiple correlation are confirmed by the wavelet multiple cross-correlation. For scale 7, we note an asymmetry (negative-skewness) which means that on this scale, the EGX30 lags the others indices. Compared to other studies of stock markets integration using the same methods in Europe and Asia (Tiwari et al., 2013; Fernández-Macho, 2012), African stock markets are far from integrated. For the construction of the confidence intervals, we used the estimators proposed by Whitcher et al. (2000). They are robust to the non-normality distribution.

Fig. 2: Wavelet Multiple Cross-Correlation of the six major African stock markets returns.



In the top left the potential lead/lag market. The dotted lines correspond to the Upper (U) and Lower (L) bounds of the 95% confidence interval.

Tab. 3: Lag order selection of the VAR model.

Lag Order					
	1	2	3	4	5
AIC(n)	-6.175581e+012*	-6.175484e+01	-6.175995e+01	-6.175811e+01	-6.176096e+01
BIC(n)	-6.171620e+01*	-6.168552e+01	-6.166093e+01	-6.162939e+01	-6.160253e+01

To go further, we apply the Diebold and Yilmaz (2012) method to the data at different timescales. The analysis of Tab. 4 shows that for the scales D_1 to D_7, the normality hypothesis is not rejected while for the S7 scale it is rejected. We can not therefore use the scale S_7 in view of the stationarity hypothesis of the VAR models. To determine the optimum VAR lag, we use the AIC and the BIC on the original returns data (see Tab. 3). Based on the different criteria, we have chosen one lag.

Tab. 4: Stationarity test results from scale 1 to scale 7.

Variables	ADF(pvalue)	KPSS(pvalue)	PP (pvalue)
Scale1 (D_1)			
TOP40	0.01	0.1	0.01
EGX30	0.01	0.1	0.01
MADEX	0.01	0.1	0.01
NGSE	0.01	0.1	0.01
NSE20	0.01	0.1	0.01
BRVM10	0.01	0.1	0.01
Scale2 (D_2)			
TOP40	0.01	0.1	0.01
EGX30	0.01	0.1	0.01
MADEX	0.01	0.1	0.01
NGSE	0.01	0.1	0.01
NSE20	0.01	0.1	0.01
BRVM10	0.01	0.1	0.01
Scale3 (D_3)			
TOP40	0.01	0.1	0.01
EGX30	0.1	0.1	0.01
MADEX	0.01	0.1	0.01
NGSE	0.01	0.1	0.01
NSE20	0.01	0.1	0.01
BRVM10	0.01	0.1	0.01
Scale4 (D_4)			
TOP40	0.01	0.1	0.01
EGX30	0.01	0.1	0.01
MADEX	0.01	0.1	0.01
NGSE	0.01	0.1	0.01
NSE20	0.01	0.1	0.01
BRVM10	0.01	0.1	0.01
Scale5 (D_5)			
TOP40	0.01	0.1	0.01
EGX30	0.01	0.1	0.01
MADEX	0.01	0.1	0.01
NGSE	0.01	0.1	0.01
NSE20	0.01	0.1	0.01
BRVM10	0.01	0.1	0.01
Scale6 (D_6)			
TOP40	0.01	0.1	0.01
EGX30	0.01	0.1	0.01
MADEX	0.01	0.1	0.01
NGSE	0.01	0.1	0.01
NSE20	0.01	0.1	0.01
BRVM10	0.01	0.1	0.01
Scale7 (D_7)			
TOP40	0.01	0.1	0.01
EGX30	0.01	0.1	0.01
MADEX	0.01	0.1	0.01
NGSE	0.01	0.1	0.01
NSE20	0.01	0.1	0.01
BRVM10	0.01	0.1	0.01
Scale7 (S_7)			
TOP40	0.33	0.01	0.92
EGX30	0.53	0.01	0.99
MADEX	0.38	0.01	0.99
NGSE	0.26	0.01	0.99
NSE20	0.16	0.01	0.99
BRVM10	0.01	0.01	0.99

The analysis of Tab. 5[25] results shows that integration varies according to the scales. The spillovers between stock markets are weak and increase as scales increase. Note that the spillovers are down to scale 5. The results confirm those obtained by the WMC. The WMCC showed that at scale 1, the South Africa stock market was a potential leader or follower of other African financial markets. The scale 1 (intra-week) of the spillovers table shows that the Egyptian market is the one that shares most of the spillovers. However, it should be noted that the majority of the Egyptian spillovers are mainly directed towards South Africa stock exchange.

The spillovers from South Africa to other markets are higher than those of Egypt. The South African financial market thus influences the overall African financial market more than the Egyptian financial market. At the other scales, the Egyptian financial market is the most influential market[26] at the African level but is

[25]Spillovers table covering the full sample
[26]The stock market that shares most of the spillovers

Tab. 5: Spillovers table of stock markets returns at different scales: January 2, 2003 - August 17, 2016

Scale 1	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	93.26	5.66	0.13	0.20	0.62	0.13	6.74
Egypt	1.91	97.51	0.28	0.08	0.17	0.06	2.49
Morocco	1.35	1.09	95.62	1.13	0.45	0.36	4.38
Nigeria	0.14	0.21	0.28	98.84	0.33	0.21	1.16
Kenya	0.65	0.07	0.15	0.11	98.60	0.43	1.40
WAEMU	0.42	0.57	0.62	0.36	1.17	96.86	3.14
To others	4.46	7.59	1.45	1.88	2.75	1.19	Total Spillovers= 19.32

Scale 2	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	93.40	4.77	1.08	0.64	0.10	0.01	6.60
Egypt	3.36	93.97	0.51	0.57	1.45	0.13	6.03
Morocco	2.23	2.59	93.69	0.43	0.52	0.54	6.31
Nigeria	1.31	3.15	0.70	92.84	1.31	0.70	7.16
Kenya	0.38	4.30	0.30	1.56	92.26	1.20	7.74
WAEMU	0.21	0.32	0.86	1.77	0.53	96.32	3.68
To others	7.49	15.13	3.45	4.96	3.90	2.58	Total Spillovers= 37.51

Scale 3	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	78.91	16.34	2.46	1.33	0.44	0.52	21.09
Egypt	22.08	72.22	1.95	2.24	1.36	0.15	27.78
Morocco	5.22	6.87	84.31	1.85	1.17	0.59	15.69
Nigeria	5.25	6.06	1.57	82.30	0.25	4.57	17.70
Kenya	2.56	4.77	3.35	0.25	86.20	2.88	13.80
WAEMU	0.71	0.02	1.64	4.12	4.73	88.78	11.22
To others	35.82	34.05	10.96	9.79	7.95	8.71	Total Spillovers= 107.28

Scale 4	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	62.98	18.92	12.37	0.56	4.76	0.41	37.02
Egypt	17.56	74.15	1.43	1.11	3.19	2.56	25.85
Morocco	3.13	5.56	74.30	4.55	2.95	9.51	25.70
Nigeria	6.87	2.28	0.31	88.80	1.73	0.00	11.20
Kenya	21.41	14.51	1.75	2.25	57.66	2.42	42.34
WAEMU	0.09	1.42	1.87	0.13	4.03	92.45	7.55
To others	49.06	42.70	17.74	8.59	16.67	14.90	Total Spillovers= 149.66

Scale 5	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	78.30	13.98	2.38	1.60	3.69	0.05	21.70
Egypt	10.03	83.68	0.61	4.04	1.53	0.11	16.32
Morocco	5.42	3.49	77.35	3.31	0.02	10.40	22.65
Nigeria	7.20	12.03	0.51	78.52	1.67	0.07	21.48
Kenya	8.58	14.45	0.08	2.73	73.92	0.24	26.08
WAEMU	0.64	1.22	3.08	0.04	2.55	92.47	7.53
To others	31.87	45.17	6.66	11.72	9.46	10.87	Total Spillovers= 115.75

Scale 6	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	70.70	20.41	0.44	1.01	7.16	0.27	29.30
Egypt	11.28	75.61	1.60	1.21	10.09	0.21	24.39
Morocco	1.25	9.93	81.99	0.03	1.10	5.70	18.01
Nigeria	2.67	11.38	0.00	81.14	3.81	1.00	18.86
Kenya	5.02	22.63	0.10	7.33	64.86	0.06	35.14
WAEMU	3.01	4.44	0.83	4.32	1.29	86.11	13.89
To others	23.22	68.79	2.98	13.91	23.46	7.24	Total Spillovers= 139.59

Scale 7	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	68.69	16.41	1.22	0.22	9.31	4.15	31.31
Egypt	4.93	71.14	4.89	3.60	13.95	1.49	28.86
Morocco	2.17	34.63	50.21	0.33	11.67	0.99	49.79
Nigeria	0.76	8.54	0.74	84.21	5.10	0.66	15.79
Kenya	4.59	31.76	3.85	3.05	56.73	0.02	43.27
WAEMU	7.73	13.72	1.40	3.22	0.01	73.92	26.08
To others	20.18	105.06	12.10	10.41	40.03	7.31	Total Spillovers= 195.10

not the most open[27]. At almost all scales, the Kenyan market is the most open financial market. The WAEMU has the least open and least influential financial market of the sample.

For a more focused analysis of the stock market integration, we will subdivide our study period into 4 sub-periods. The first (2003-2007) takes into account the period before the U.S financial crisis (see Tab. 6)

The second (2007-2010) covers the period of the American financial crisis (see Tab. 7). The third (2010-2012) covers the period of European debt crisis (see Tab. 8). Finally, the fourth (2012-2016) and last period covers a period of strong growth in African financial markets, but also a period of increasing measures to integrate these markets (see Tab. 9). The period before the U.S financial crisis will serve as a basis for comparison. It will show whether spillovers at different scales between financial markets have increased over time.

The analysis of Tab. 6, Tab. 7, Tab. 8 and Tab. 9 showed that spillovers between stock markets are generally high in times of financial crisis.

During the U.S financial crisis, the spillovers between African stock markets peaked. The U.S financial crisis

[27] The stock market that receives most of the spillovers

Tab. 6: Spillovers table of stock markets returns at different scales: January 6, 2003 - April 26, 2007

Scale 1	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	92.87	3.21	0.85	2.46	0.01	0.60	7.13
Egypt	0.83	96.57	1.31	0.22	0.41	0.66	3.43
Morocco	2.25	3.68	90.30	1.19	1.32	1.26	9.70
Nigeria	0.92	1.75	2.67	94.39	0.07	0.20	5.61
Kenya	0.10	0.59	0.61	0.09	97.05	1.55	2.95
WAEMU	2.19	7.73	2.54	1.13	0.32	86.09	13.91
To others	6.29	16.97	7.99	5.08	2.12	4.28	Total Spillovers= 42.73
Scale 2	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	93.39	3.43	1.69	0.19	0.62	0.69	6.61
Egypt	0.96	95.07	0.86	1.29	0.17	1.64	4.93
Morocco	3.93	5.75	85.13	1.20	0.87	3.13	14.87
Nigeria	0.27	9.42	0.46	81.73	4.47	3.64	18.27
Kenya	0.82	0.80	0.10	2.59	92.42	3.27	7.58
WAEMU	1.04	2.95	4.61	3.83	0.94	86.64	13.36
To others	7.02	22.36	7.72	9.09	7.06	12.37	Total Spillovers= 65.63
Scale 3	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	78.47	3.99	3.95	5.33	7.91	0.35	21.53
Egypt	12.18	81.33	2.20	1.88	2.09	0.33	18.67
Morocco	13.51	3.71	77.67	1.03	2.57	1.51	22.33
Nigeria	0.82	16.85	0.09	81.63	0.49	0.12	18.37
Kenya	0.84	1.75	10.08	0.24	85.03	2.07	14.97
WAEMU	0.41	1.76	2.30	0.42	5.98	89.13	10.87
To others	27.75	28.06	18.61	8.90	19.04	4.39	Total Spillovers= 106.74
Scale 4	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	60.98	26.44	10.92	0.12	0.87	0.67	39.02
Egypt	11.03	72.32	3.64	0.00	12.08	0.93	27.68
Morocco	20.64	7.91	48.69	0.97	4.33	17.47	51.31
Nigeria	10.43	0.30	4.21	69.46	8.25	7.35	30.54
Kenya	4.87	10.35	10.47	6.04	64.78	3.49	35.22
WAEMU	1.39	1.38	3.67	9.42	14.69	69.45	30.55
To others	48.36	46.38	32.91	16.54	40.22	29.91	Total Spillovers= 214.32
Scale 5	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	54.82	18.53	12.14	0.67	9.39	4.45	45.18
Egypt	3.35	75.69	1.44	2.27	3.64	13.62	24.31
Morocco	17.68	12.03	52.63	1.63	0.73	15.30	47.37
Nigeria	1.93	12.63	3.62	78.95	1.58	1.30	21.05
Kenya	1.44	14.76	0.69	2.44	79.64	1.03	20.36
WAEMU	0.95	11.56	3.16	1.09	0.36	82.88	17.12
To others	25.34	69.50	21.05	8.10	15.71	35.70	Total Spillovers= 175.40
Scale 6	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	74.60	13.22	6.67	3.33	0.85	1.34	25.40
Egypt	6.50	52.43	12.48	10.98	8.89	8.71	47.57
Morocco	4.40	36.20	43.72	8.04	1.04	6.60	56.28
Nigeria	0.46	12.60	3.13	66.05	10.76	7.01	33.95
Kenya	0.05	5.21	0.45	25.50	67.86	0.92	32.14
WAEMU	0.03	8.22	0.89	5.34	0.29	85.23	14.77
To others	11.44	75.45	23.63	53.18	21.83	24.59	Total Spillovers= 210.12
Scale 7	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	32.54	45.29	1.16	1.41	18.05	1.56	67.46
Egypt	28.08	49.48	0.29	3.86	14.61	3.68	50.52
Morocco	1.24	0.95	28.81	44.15	1.85	23.01	71.19
Nigeria	4.09	9.12	11.51	45.97	0.18	29.13	54.03
Kenya	25.76	35.18	1.25	0.73	34.93	2.16	65.07
WAEMU	4.44	11.29	6.47	36.17	0.32	41.31	58.69
To others	63.61	101.83	20.68	86.31	35.00	59.54	Total Spillovers= 366.97

is characterized by a general increase in relations between the African financial markets. Indeed, the African financial markets having been weakly affected by the crisis have surely increased exchanges between them. The most influential markets are the South African (intra-week to week and monthly) and Kenyan (quarterly to bi-annual scales) stock markets. Concerning the most open markets, Morroco has is the most open stock market at large scales (monthly to bi-annual). At small and medium scales, the most open financial markets vary according to them (see Tab. 7) . However, it should be noted, that the WAEMU market is the most open at scale 2.

The period of the European debt crisis is also characterized by an increase in the spillovers between the stock markets. However, it is not as strong as those of the U.S financial crisis. Across all scales, we are seeing that the Kenyan stock market is the most open market of our panel on monthly and bi-annual scales. The opening of the stock markets differs according to the scale (see Tab. 8). From the intra-week to the monthly scale, Morocco has the least influential stock market. During this crisis, we note that the South African stock

Tab. 7: Spillovers table of stock markets returns at different scales: May 2, 2007 - January 4, 2010

Scale 1	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	87.29	8.92	0.79	0.89	1.70	0.42	12.71
Egypt	6.29	92.74	0.16	0.26	0.51	0.04	7.26
MADEX	6.39	1.54	89.65	0.67	0.23	1.52	10.35
Nigeria	1.45	1.52	0.98	94.28	0.43	1.35	5.72
Kenya	3.58	0.57	0.76	1.09	92.01	1.98	7.99
WAEMU	0.19	1.34	1.70	0.06	6.60	90.11	9.89
To others	17.90	13.89	4.38	2.97	9.47	5.32	Total Spillovers= 52.93
Scale 2	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	86.98	4.72	4.07	2.43	1.20	0.60	13.02
Egypt	4.77	86.44	1.29	2.32	4.41	0.76	13.56
MADEX	5.85	4.22	87.13	0.98	1.18	0.63	12.87
Nigeria	2.57	1.93	0.54	92.22	0.94	1.80	7.78
Kenya	2.50	9.86	1.01	0.08	86.15	0.39	13.85
WAEMU	11.61	6.41	1.37	0.47	3.36	76.78	23.22
To others	27.30	27.14	8.28	6.29	11.09	4.18	Total Spillovers= 84.29
Scale 3	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	58.95	21.59	5.33	9.06	1.95	3.12	41.05
Egypt	31.16	56.09	4.27	3.90	2.70	1.88	43.91
MADEX	7.41	12.82	65.86	7.97	2.33	3.61	34.14
Nigeria	2.64	1.50	5.11	74.89	5.58	10.28	25.11
Kenya	2.57	6.33	2.43	12.47	69.18	7.03	30.82
WAEMU	5.50	7.62	2.41	10.90	14.41	59.17	40.83
To others	49.28	49.85	19.54	44.29	26.97	25.92	Total Spillovers= 215.85
Scale 4	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	47.54	16.84	18.16	1.99	2.21	13.25	52.46
Egypt	21.77	58.84	8.48	3.63	7.14	0.13	41.16
MADEX	12.53	2.34	59.39	5.29	10.94	9.52	40.61
Nigeria	15.38	9.78	0.26	66.52	5.74	2.31	33.48
Kenya	23.42	9.66	1.37	29.86	34.19	1.49	65.81
WAEMU	24.77	5.35	6.33	7.33	0.80	55.42	44.58
To others	97.87	43.98	34.61	48.10	26.83	26.71	Total Spillovers= 278.09
Scale 5	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	56.53	5.20	17.88	1.29	10.22	8.88	43.47
Egypt	29.08	44.06	3.61	7.25	1.72	14.28	55.94
MADEX	23.48	9.85	37.90	1.06	17.81	9.90	62.10
Nigeria	1.20	3.88	0.31	68.32	14.67	11.63	31.68
Kenya	16.82	9.02	5.34	5.74	59.72	3.36	40.28
WAEMU	11.09	19.65	10.60	9.85	0.84	47.97	52.03
To others	81.68	47.59	37.74	25.19	45.26	48.04	Total Spillovers= 285.50
Scale 6	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	69.18	1.95	2.49	0.54	20.93	4.91	30.82
Egypt	1.96	55.90	6.09	10.29	22.33	3.44	44.10
MADEX	13.23	0.43	47.83	23.85	7.10	7.56	52.17
Nigeria	2.67	1.16	28.87	57.20	9.06	1.03	42.80
Kenya	10.74	7.11	11.54	7.67	61.54	1.39	38.46
WAEMU	11.38	11.59	2.56	3.03	22.59	48.85	51.15
To others	39.98	22.24	51.54	45.39	82.01	18.33	Total Spillovers= 259.5
Scale 7	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	53.77	4.32	2.01	35.18	1.89	2.83	46.23
Egypt	4.81	41.88	19.14	11.62	22.50	0.04	58.12
MADEX	3.63	36.59	21.75	14.24	23.71	0.07	78.25
Nigeria	2.30	21.15	11.91	41.37	22.98	0.30	58.63
Kenya	0.84	21.96	12.11	20.44	38.44	6.21	61.56
WAEMU	0.48	0.42	0.09	6.35	42.74	49.93	50.07
To others	12.06	84.43	45.26	87.84	113.83	9.44	Total Spillovers= 352.86

market becomes one of the least open markets and is even the least influential at scale 7 (bi-annual). According to Sugimoto et al. (2014) the spillovers from European stock markets to Africa stock markets increased. This could explain the lack of spillovers between the South African market and the other African stock markets. Indeed the South African stock exchange being attractive, it could have been a solid opportunity to diversify capital for European stock markets.

Concerning the latter period[28](see Tab. 9), across all scales the spillovers are smaller than those in times of crisis. In comparison with the pre-crisis period, we find that at allmost all scales, the spillovers are falling excepted at scales 3 and 5 (respectively fortnightly and monthly to quarterly). Nigeria and Egypt have the least open stock markets. However, we found that the influence of the Nigerian stock market relative to the pre-crisis period (see Tab. 6) increased significantly at scales 3 to 5. Across almost all scales, the Egypt's stock market remains the most influential. In addition, at scale 7, the WAEMU stock market becomes the most influential,

[28]strong stock markets development and increased openness measures

Tab. 8: Spillovers table of stock markets returns at different scales: January 5, 2010 - December 31, 2012

Scale 1	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	92.04	4.24	1.00	0.95	0.96	0.80	7.96
Egypt	3.36	95.32	0.03	0.94	0.34	0.01	4.68
MADEX	1.25	0.52	88.48	5.14	4.39	0.22	11.52
Nigeria	1.74	1.48	0.35	89.73	4.07	2.63	10.27
Kenya	0.55	1.15	2.15	7.20	85.80	3.15	14.20
WAEMU	0.97	0.24	0.03	0.79	0.94	97.03	2.97
To others	7.87	7.64	3.56	15.02	10.70	6.82	Total Spillovers= 51.60
Scale 2	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	90.46	5.67	0.10	2.61	0.59	0.57	9.54
Egypt	4.94	86.51	1.06	2.02	5.14	0.32	13.49
MADEX	0.47	2.17	94.91	1.97	0.16	0.32	5.09
Nigeria	4.81	2.41	2.36	85.40	4.92	0.11	14.60
Kenya	1.68	10.76	0.02	9.79	74.34	3.40	25.66
WAEMU	0.28	0.71	0.28	0.13	4.19	94.41	5.59
To others	12.18	21.72	3.81	16.52	15.01	4.72	Total Spillovers= 73.95
Scale 3	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	65.22	17.33	1.12	1.91	12.82	1.60	34.78
Egypt	8.91	80.81	1.26	2.49	4.31	2.22	19.19
MADEX	3.47	13.30	73.16	3.13	0.16	6.77	26.84
Nigeria	0.76	7.99	3.59	75.37	8.48	3.81	24.63
Kenya	16.38	17.44	0.27	14.58	51.00	0.33	49.00
WAEMU	1.66	7.08	4.34	8.94	0.39	77.59	22.41
To others	31.18	63.14	10.58	31.05	26.16	14.74	Total Spillovers= 176.84
Scale 4	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	61.50	12.28	2.34	11.72	3.96	8.20	38.50
Egypt	12.57	70.87	1.08	3.47	4.58	7.43	29.13
MADEX	0.98	34.65	55.66	3.53	4.43	0.76	44.34
Nigeria	3.28	26.08	0.83	63.24	5.45	1.12	36.76
Kenya	16.57	36.30	0.83	4.55	34.65	7.10	65.35
WAEMU	7.62	12.05	1.67	1.06	4.94	72.66	27.34
To others	41.01	121.36	6.76	24.33	23.36	24.61	Total Spillovers= 241.42
Scale 5	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	81.46	4.17	0.90	8.88	3.66	0.93	18.54
Egypt	7.97	72.08	2.17	8.97	4.93	3.88	27.92
MADEX	6.28	27.56	48.30	9.54	2.91	5.41	51.70
Nigeria	4.09	19.89	2.30	41.10	30.30	2.32	58.90
Kenya	9.09	16.96	1.10	11.85	57.70	3.29	42.30
WAEMU	5.27	1.85	13.56	3.06	16.25	60.00	40.00
To others	32.70	70.44	20.03	42.30	58.05	15.82	Total Spillovers= 239.35
Scale 6	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	78.67	0.50	11.74	8.09	0.43	0.57	21.33
Egypt	2.38	73.14	0.53	14.93	7.22	1.80	26.86
MADEX	1.45	2.01	70.23	14.44	1.18	10.70	29.77
Nigeria	8.19	18.49	15.32	46.68	4.28	7.03	53.32
Kenya	2.00	37.01	0.23	18.97	39.33	2.47	60.67
WAEMU	3.23	1.24	23.53	22.45	0.50	49.06	50.94
To others	17.26	59.24	51.35	78.88	13.60	22.57	Total Spillovers= 242.90
Scale 7	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	30.33	62.21	2.72	0.75	1.25	2.75	69.67
Egypt	2.94	90.36	1.25	4.38	0.13	0.93	9.64
MADEX	0.54	0.14	55.43	40.12	2.18	1.59	44.57
Nigeria	0.34	12.36	12.76	57.20	9.99	7.35	42.80
Kenya	0.02	0.15	8.36	3.65	60.94	26.88	39.06
WAEMU	0.62	1.37	0.23	4.57	42.10	51.12	48.88
To others	4.46	76.22	25.31	53.46	55.65	39.50	Total Spillovers= 254.62

confirming the recent growth of the BRVM[29].

Finally, we note that the spillovers at different scales between the financial markets vary according to the economic and financial environment. The relationship between African financial markets increases in times of crisis, thus confirming a contagion phenomenon during these periods of instability (see Forbes and Rigobon, 2002; McAleer and Nam, 2005). The comparison of the sub-periods from 2003-2007 and from 2012-2016 showed that the spillovers between African financial markets at almost all scales have declined in recent years. This implies that despite the reforms, the African stock markets integration tends to decline confirming the results of Collins and Biekpe (2003b) (see Section 2. These low spillovers are understandable. In recent years, the African stock markets have increased the openness measures both among themselves and with the outside (see ASEA, 2015). These low spillovers could result from an increase in trade with the outside[30] rather than between them. However, we are seeing some progress. At the 3rd and 5th scales (respectively fortnightly and monthly

[29] www.african-markets.com

[30] world financial markets are more attractive and politically stable

Tab. 9: Spillovers table of stock markets returns at different scales: January 2, 2012 - August 17, 2016

Scale 1	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	87.40	8.32	0.94	2.26	0.41	0.66	12.60
Egypt	2.28	92.49	0.17	4.69	0.08	0.29	7.51
MADEX	1.07	4.07	93.92	0.18	0.66	0.11	6.08
Nigeria	0.62	2.14	0.06	95.77	0.24	1.16	4.23
Kenya	0.92	0.16	0.57	0.41	93.99	3.95	6.01
WAEMU	1.09	2.04	0.05	1.57	0.97	94.29	5.71
To others	5.98	16.73	1.79	9.11	2.37	6.17	Total Spillovers= 42.15
Scale 2	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	86.49	8.33	0.92	3.50	0.61	0.16	13.51
Egypt	5.59	89.83	0.47	3.48	0.14	0.50	10.17
MADEX	2.39	1.10	93.57	1.26	0.82	0.86	6.43
Nigeria	5.51	4.95	0.35	87.25	0.64	1.31	12.75
Kenya	2.77	2.84	1.51	2.53	90.31	0.03	9.69
WAEMU	1.64	0.67	0.60	3.44	0.05	93.60	6.40
To others	17.90	17.89	3.84	14.22	2.26	2.85	Total Spillovers= 58.96
Scale 3	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	68.98	18.25	2.61	4.28	4.84	1.05	31.02
Egypt	11.71	68.26	0.03	8.00	10.99	1.01	31.74
MADEX	1.48	9.26	77.63	10.32	0.55	0.76	22.37
Nigeria	6.61	10.77	0.32	74.73	2.47	5.09	25.27
Kenya	21.65	24.68	0.60	9.62	43.38	0.07	56.62
WAEMU	1.95	4.75	0.39	7.50	0.79	84.62	15.38
To others	43.40	67.72	3.94	39.73	19.63	7.99	Total Spillovers= 182.40
Scale 4	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	73.40	6.26	9.80	6.74	1.52	2.28	26.60
Egypt	8.10	80.05	0.46	0.60	9.50	1.29	19.95
MADEX	2.17	2.55	80.44	6.62	0.16	8.06	19.56
Nigeria	4.96	4.20	4.90	84.68	0.33	0.94	15.32
Kenya	28.40	2.11	0.11	11.03	57.27	1.07	42.73
WAEMU	1.62	5.52	0.95	4.28	10.94	76.70	23.30
To others	45.25	20.64	16.22	29.27	22.46	13.64	Total Spillovers= 147.47
Scale 5	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	72.94	16.86	0.08	4.98	2.88	2.26	27.06
Egypt	2.21	84.69	5.77	0.06	2.14	5.13	15.31
MADEX	0.54	12.48	75.19	5.13	0.79	5.87	24.81
Nigeria	5.73	1.04	4.09	75.32	12.02	1.80	24.68
Kenya	6.09	0.35	3.19	22.73	64.95	2.68	35.05
WAEMU	16.56	15.91	0.29	12.10	7.99	47.15	52.85
To others	31.13	46.64	13.42	45.00	25.82	17.74	Total Spillovers= 179.76
Scale 6	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	79.36	6.92	0.01	9.01	3.75	0.95	20.64
Egypt	5.77	87.41	0.44	0.17	3.82	2.39	12.59
MADEX	0.90	6.02	56.59	25.76	6.66	4.07	43.41
Nigeria	5.70	0.20	4.84	81.14	0.00	8.11	18.86
Kenya	0.82	42.55	9.26	0.30	45.54	1.52	54.46
WAEMU	5.14	2.74	6.04	21.38	2.27	62.43	37.57
To others	18.32	58.42	20.59	56.63	16.51	17.04	Total Spillovers= 187.52
Scale 7	South Africa	Egypt	Morocco	Nigeria	Kenya	WAEMU	From others
South Africa	57.20	1.70	10.17	3.87	23.99	3.06	42.80
Egypt	0.39	43.58	4.07	13.35	5.30	33.31	56.42
MADEX	18.98	11.74	24.15	0.23	19.92	24.97	75.85
Nigeria	9.47	10.95	0.66	72.00	2.08	4.84	28.00
Kenya	27.24	4.55	7.80	5.68	41.99	12.73	58.01
WAEMU	1.75	24.92	7.77	7.56	8.55	49.44	50.56
To others	57.84	53.87	30.48	30.71	59.83	78.92	Total Spillovers=311.64

to quarterly) of the last period, spillovers between African stock markets have increased compared to those of the pre-crisis period (see Tab. 9). This means that integration between African financial markets although weak is rising on fortnightly and quarterly to monthly scales. The financial information is faster than before between African financial markets. This implies an improvement in the transmission channels (development of financial institutions) between African financial markets.

5 Conclusion

This paper examines the relationships between the 6 largest African stock markets (South Africa, Egypt, Morocco, Nigeria, Kenya, and WAEMU) at different timescales. In particular, we want to see whether the numerous measures and reforms put in place for a better integration of these financial markets have been effective.First, we used the Wavelet Multiple Correlation (WMC) and the Wavelet Multiple Cross-Correlation (WMCC) proposed by Fernández-Macho (2012) to measure the level of integration between the six African stock markets at seven timescales. Then, we used the Diebold and Yilmaz (2012) spillovers index on the 7 timescales to more precisely determine the relationships between these financial markets.

The results show that African stock markets are weakly integrated. However, this low integration almost located at small timescales (intra-week to monthly) tends to grow at large (bi-annual) time scales. Across all scales, with the exception of the intra-week scale or it is the South African stock market, the Egyptian stock market is the potential leader or follower of other African markets. At the bi-annual scale, the Egyptian market is indeed a follower of other markets, which lags the others stock markets. The crisis periods (the US financial crisis and the European debt crisis) are characterized by an increase of spillovers between African financial markets. The highest spillovers are localized during the U.S financial crisis confirming the contagion between financial markets in times of financial crisis (see Forbes and Rigobon, 2002; McAleer and Nam, 2005). In contrast, the spillovers between African financial markets have been declining in recent years at almost all scales except at scales 3 and 5 (fortnightly and monthly to quarterly) where they increase.

We can conclude that despite all the reforms of recent years for better integration, African stock markets are far from being integrated. We are seeing a decline in relationships between African stock markets in recent years. However, it should be noted that increased spillovers at medium scales (fortnightly and monthly to quarterly) could mean a slight improvement in the transmission of financial information and hence of African financial institutions.

However, this decline in integration despite a slightly faster financial flow seems logical. This can be explained by the fact that African stock markets have become viable ways of diversifying capital for world financial markets (see Raleigh, 2014). Financial exchanges with the outside world may have been increased to the detriment of regional exchanges. This very weak integration of African stock markets offers great opportunities for diversification mostly at small scales.

Findings from this paper are relevant for diversification strategies and policy makers. The competent authorities should, therefore, make further efforts in the stock markets integration, but also better promote trade between African stock exchanges.

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