Beginning an African Stock Markets Integration? A Wavelet Analysis

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Abstract

This paper studies the integration of the most six largest African stock markets in term of capital using the Wavelet Multiple Correlation (WMC) and the Wavelet Multiple Cross-Correlation (WMCC) proposed by Fernández-Macho (2012). These methods are used to study simultaneously the correlation between several variables at different time scales. They have some advantages over previous models. Results show that the integration between the six stock markets returns remains low but tends to increase gradually in time and is greater in the long run. A diversified investment opportunity is possible in these stock markets at all scales.

Keywords: African Stock Markets, Stock Markets Integration, Wavelet Multiple Correlation, Wavelet Multiple Cross-Correlation

JEL Classification: C4, F3, G1

1. Introduction

In recent decades, stock markets in Africa boomed. Many stock markets appeared in various countries and some have even attracted attention internationally because of their dynamism. The number of stock markets increased from 12 to 23 today. Between the years 2007 and 2009, more than $10 billions capital were identified in 18 stock exchanges of 200 new companies IPO[1]. The African financial markets have experienced incredible growth. Typical examples are the Ghana Stock Exchange elected the best performing market in the world in 2004, the IPO of Safaricom at Nairobi in 2007 with a market

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[1] Initial Public Offering

capitalization similar to some companies listed on New York Stock Exchange, Nigeria, with over $8 billions invested on traded companies soon over the period 2007-2009 to mention only these. The market capitalization of the 10 largest markets in Africa has tripled from 2002 to 2008.

This significant increase in financial platforms and the evolution of some of them to international standard show that stock markets are beginning to impact our African economies. These notable advanced of African stock markets have raised the matter of their integration.

The analysis of co-movement between financial markets has gone through many developments especially with the advent of financial crisis. Several authors such as Reinhart and Calvo (1996) are interested in Latin markets, Baig and Goldfain (1998, 2000) in Russian and Brazilian markets and thereafter on Asian markets, Granger and al. (2000) specifically in Asian stock prices.

Chakrabarti and Roll (2002) study the presence of correlation between major world stock markets, Engle and al. (1990) tackled the distribution of volatility between stock markets, Forbes and Rigobon (2002), McAleer and Nam (2005) focused on the co-movement in the financial crisis. This researches in their majority demonstrated mostly the presence more or less of contagion among emerging or developed stock markets.

Some studies are interested to African stock markets. Collins and Biekpe (2003a,b), Wang and al. (2003) were interested in unveiling correlation between different African stock markets during and after the Asian crisis of 1997. Adjasi and Biekpe (2006) used cointegration and error-correction modelling to study the link between African stock markets by their causality in the short and long term. Emenalo (2009) focused on the link between African frontier markets and emerging markets, Agyei-Ampomah (2008) studied the linkage between different African stock exchanges and Morara (2011) considered the relationship between African boundary markets and the developed world markets. Boamah (2013) was interested in integration of African stock markets with outside. All these studies agreed that African financial markets are poorly integrated with each other and with the outside world except for African emerging financial markets like South Africa and Egypt.

All these papers have some limitations because they analyze the stock markets co-movement just in time perspective. Recently a new approach to analyze correlation between variables based on the wavelet theory appeared. It uses interesting features of the wavelet transform to allow a simultaneous time and frequency analysis to measure the interdependence between variables at many time scales. This approach is more indicative of financial markets behavior. In world markets co-movement, these methods are illustrated by works such as Fernández-Macho (2012) in Europe, Tiwari and al. (2013) in Asia, Loh (2013) between Asia and the outside, Graham and Nikkinen (2011), Graham and 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[2] and outside, Rua and Nunes (2009) between several global financial markets.

In our paper, we apply two wavelet methods proposed by Fernández-Macho (2012), the Wavelet Multiple Correlation and the Wavelet Multiple Cross-Correlation to study the relationship between the 6 most significant African stock markets in term of capital. These methods are advantageous because they permit first to have in two plots, the multiple correlation and multiple cross-correlation within the multivariate set of different time scales for many stock markets, then they protect against type 1 errors and finally permit to avoid spurious correlation obtained from the pair wise correlations within the multivariate set of stock markets. This work follows the same logic than cited above (Collins and Biekpe, 2003a,b; Wang and al., 2003) but is innovative in that to our knowledge is the first analysis in time and frequency even relations between only African stock markets.

The rest of the study is structured as follows. Section 2 reviews a brief literature on wavelet application to stock markets co-movement. Section 3 details the methodology used to inspect the six African stock markets integration. Section 4 examines the data used and empirical results and Section 5 concludes.

2. Literature Review

Literature on stock markets co-movement using wavelet methods is relatively new. However, a number of researchers have delved into the area and contributing immensely to its development. One of the pioneers is Gallegati (2005) who studied the co-movement relationship among five major MENA , the U.S[3] and Eurozone stock markets in a scale by scale basis through the Maximal Overlap Discrete Wavelet Transform (MODWT). The wavelet correlation analysis showed that MENA stock markets are neither regionally nor internationally integrated. We can also cite Rua and Nunes (2009) that used wavelet coherence on the stock markets integration between Germany, Japan, U.K[4] and

[2]Middle East and North Africa
[3]United States
[4]United Kingdom

U.S. They found that the japan stock market is poorly integrated with other developed financial markets and the relationship between stock markets varied with time scales. Thereafter there was Graham and Nikkinen (2011) that showed that the co-movement of Finland and emerging regions stock markets was reduced to long-term fluctuations and co-movement between Finland and developed regions stock markets in Europe, Pacific, and North America was present across all frequencies, with higher levels of co-movement in higher frequencies. Graham and al. (2012) used wavelet coherence to examine the integration of 22 emerging stock markets with the U.S. financial market. They discovered a strong contagion that differs by country. The U.S. was very correlated with Brazil, Mexico and Korea but had a low co-movement with and Egypt and Morocco. After 2006 and during the financial crisis of 2007, the co-movement between stock markets increase to relatively high frequencies. To examine the integration between MENA stock markets and US stock markets Graham and al. (2013) applied wavelet squared coherence with simulated confidence bounds. They found a weak co-movement at high frequencies (short run) but co-movement relationship increased at low frequencies (long run). Otherwise, Fernández-Macho (2012) proposed two new wavelet methods: Wavelet Multiple Correlation and Wavelet Multiple Cross-Correlation and applied them to co-movement analysis of the Eurozone stock markets. Wavelet multiple correlation put to spotlight a strong correlation near perfect among Eurozone stock markets in the long run. It also showed small inconsistencies between Eurozone markets occurring in short run and medium run that must be the consequence of the interaction of different agents with different trading horizons in mind on stock markets. Moreover, Wavelet multiple cross-correlation revealed that CAC40 tends to lead statistically the rest of the Euro market in short and medium term (one week to a month). Madaleno and Pinho (2012) was interested to the relationship between U.K, the U.S, Japan and Brazil stock markets using the coherence Morlet wavelet. They found like Rua and Nunes (2009) that the strength or weakness of co-movement depends on the time period. Recently, Tiwari and al. (2013) employed methodology of wavelet multiple correlation and multiple cross-correlation proposed by Fernández-Macho (2012) for the analysis of the integration of nine Asian stock markets. The results showed that Asian stock markets are highly integrated at low frequencies and comparatively less integrated at high frequencies. In the co-movement of 13 Asian, European and U.S stock markets returns, Loh (2013) analyzed stock markets returns using the wavelet coherence. Results shown the presence of co-movement between most of the Asia-Pacific stock markets with Europe and the U.S in the long run. However the author noted that the co-movement between markets increased at period of financial crisis. Aloui and Hkiri (2014) in their works in GCC[5] emerging stock markets co-movement used wavelet squared coherence method, found frequent changes in the pattern of the co-movements especially after crisis beginning for all the selected GCC markets at relatively high frequencies and noted an increasing strength of dependence among the GCC stock markets during crisis.

3. Methodology

We favor a temporal and frequency analysis because it permits an study at different time scales of the relationship between financial markets. These wavelet methods used to investigate the integration between African financial markets allowing a simultaneous analysis of several variables correlation were proposed by Fernández-Macho (2012). These methods use discrete wavelet and present themselves as follows.

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 DWT[6] or MODWT[7] (Percival and Walden, 2000) at each scale λ_j for every x_{it} process. The wavelet Multiple Correlation (WMC)$\varphi_X(\lambda_j)$ can be described like one single set of multiscale 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 then calculated as

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

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

[5]Gulf Cooperation Council
[6]Discrete Wavelet Transform
[7]Maximal Overlap Discrete Wavelet Transform

of correlation between the observed values of z_i and the fitted values $\hat{z}_i$ obtained of this regression.

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

$$\varphi_X(\lambda_j) = Corr(w_{ijt}, \hat{w}_{ijt}) = \frac{Cov(w_{ijt}, \hat{w}_{ijt})}{\sqrt{Var(w_{ijt})Var(\hat{w}_{ijt})}}, \tag{2}$$

where the wavelet variances and covariance are given by

$$Cov(w_{ijt}, \hat{w}_{ijt}) = \bar{\gamma}_j = \frac{1}{T_j} \sum_{t=L_j^{-1}}^{T-1} w_{ijt}\hat{w}_{ijt}, \tag{3}$$

$$Var(w_{ijt}) = \bar{\delta}_j^2 = \frac{1}{T_j} \sum_{t=:j^{-1}}^{T-1} w_{ijt}^2, \tag{4}$$

$$Var(\hat{w}_{ijt}) = \bar{\xi}_j^2 = \frac{1}{T_j} \sum_{t=:j^{-1}}^{T-1} \hat{w}_{ijt}^2. \tag{5}$$

Here w_{ij} on the set of regressors $\{w_{kj}, k \neq i\}$ leads to maximize 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 (**??**) 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 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 (**??**) 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 wavelet correlation coefficient is given as

$$CI_{1-\alpha}(\varphi_{X,\tau}(\lambda_j)) = \tanh[\tilde{z}_j \pm \phi^{-1}_{1-\alpha/2}/\sqrt{T/2^j - 3}] \quad (6)$$

4. Data and Empirical Results

Data is composed of the main indexes of the six largest stock markets in Africa in terms of capitalization, South Africa (TOP40), Egypt (EGX30), Morocco (MADEX), Nigeria (NSE), Kenya (NSE20) and WAEMU[8] area (BRVM10). We use daily data. Data sample covers the period from 3 January 2002 to 3 October 2012 (1877 observations). Note the presence of missing data at some time due to the lack of data on certain periods for some stock markets and to the mismatch of open days between different financial markets. All data were obtained from Bloomberg database. The stock markets returns were calculated as follow.

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

where R are the returns and P the closing prices.

Several summary statistics of stock markets returns are reported in Table 1.

	TOP40	EGX30	MADEX	NSE	NSE20	BRVM10
Mean	0.0005954	0.001286	0.0004814	0.0004665	5.841e-04	0.0003572
Median	0.0012640	0.001964	0.0002518	0.0000000	7.740e-06	0.0000000
Maximum	0.1157000	0.270500	0.0667500	0.1176000	1.227e-01	0.1091000
Minimum	-0.1108000	-0.201000	-0.0826300	-0.1094000	-1.537e-01	-0.1103000
Standard Deviation	0.01726169	0.02357086	0.01155414	0.01464309	0.01426894	0.01250047
Skewness	-0.2347908	-0.0419225	-0.1218592	0.3669374	0.7623321	0.5026399
Kurtosis	4.966976	17.29609	6.831067	11.24135	23.84904	15.08582
Jarque-Bera	1953.3452	23455.5311	3665.3357	9951.9386	44772.0596	17923.5172

Table 1: Descriptive Statistics of stock markets returns.

All stock returns have a positive mean. EGX30 (Egypt) has the largest standard deviation while MADEX (Morocco) has the lowest. The majority of returns have a negative skewness. The analysis of stock returns kurtosis shows they are all leptokurtic. The Jarque-Bera statistics for all series rejects strongly the null hypothesis of normality.

[8] West African Economic and Monetary Union

To obtain Wavelet Multiple Correlation and Wavelet Multiple Cross-Correlation , we calculated the wavelet coefficients at different scales of time of our stock returns using the MODWT. We used MODWT rather than the DWT because it presents the most interesting features for analysis of data such as analyze any sample size, an invariance in the circular displacement of original series, a proper alignment of the events in the original time series with the characteristics of the multiresolution , an estimator more efficient of the wavelet variance and an ability to not be affected by the arrival of new information except for the last coefficients (Percival and Walden, 2000). 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 (Percival and Walden, 2000). Note that for MODWT, a specific choice of wavelet filter is not required. The maximum scales number of decomposition is $log_2(N)$ with N, number of observations. Nonetheless the wavelet coefficients become too small to large scales, we decided to stop to $J = 7$ decompositions with seven wavelet details (Table 2) and one wavelet smooth coefficients.

Wavelet Scales	Time Interpretation	Correlation	Time period
W_{i1}	2-4 days	0.1967787	Intraweek
W_{i2}	4-8 days	0.2907081	Week
W_{i3}	8-16 days	0.3947899	Fortnightly
W_{i4}	16-32 days	0.5075008	Monthly
W_{i5}	32-64 days	0.5467435	Monthly to Quarterly
W_{i6}	64-128 days	0.6089342	Quarterly to bi-annual
W_{i7}	128-256 days	0.7744319	Bi-annual

Table 2: Wavelet Multiple Correlation analysis.

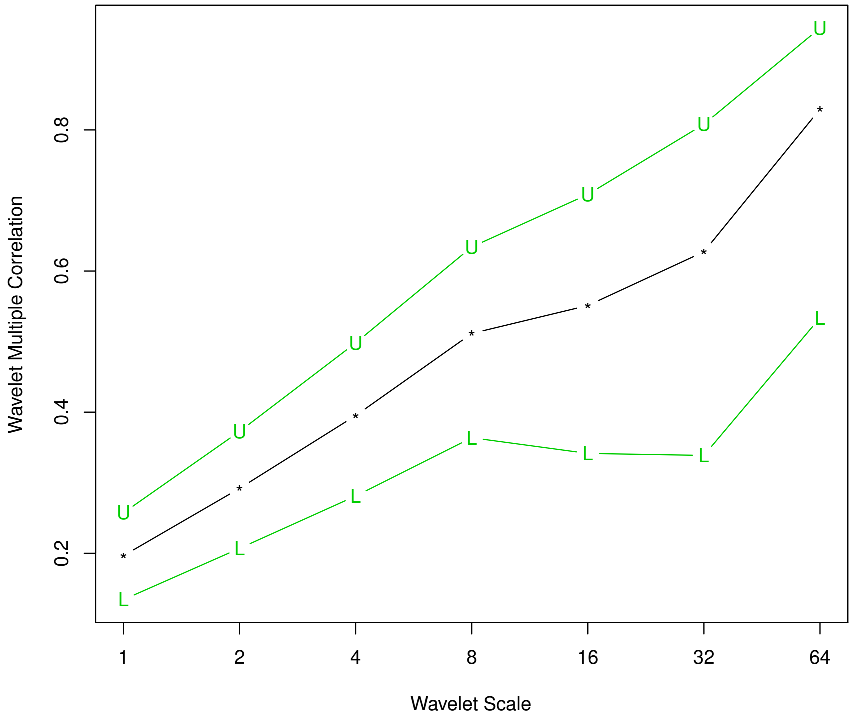

Fig. 1: Wavelet Multiple Correlation of six major African stock markets returns.

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

Fig. 1 and Table 2 analysis shows that the wavelet multiple correlation tends to grow steadily over time. The correlation between African financial markets is low to high and medium frequencies (small and medium scales) this is to say in the short term and medium term (Week, Fortnightly,. . ., Monthly to Quarterly) it ranges from 0.29 to 0.54. The integration at these scales remains low. At low frequencies (large scales), the long term, the correlation is 0.60 for quarterly to bi-annual and 0.77 to biannual. This is representative of an integration beginning between the six major African stock market returns in the long run.

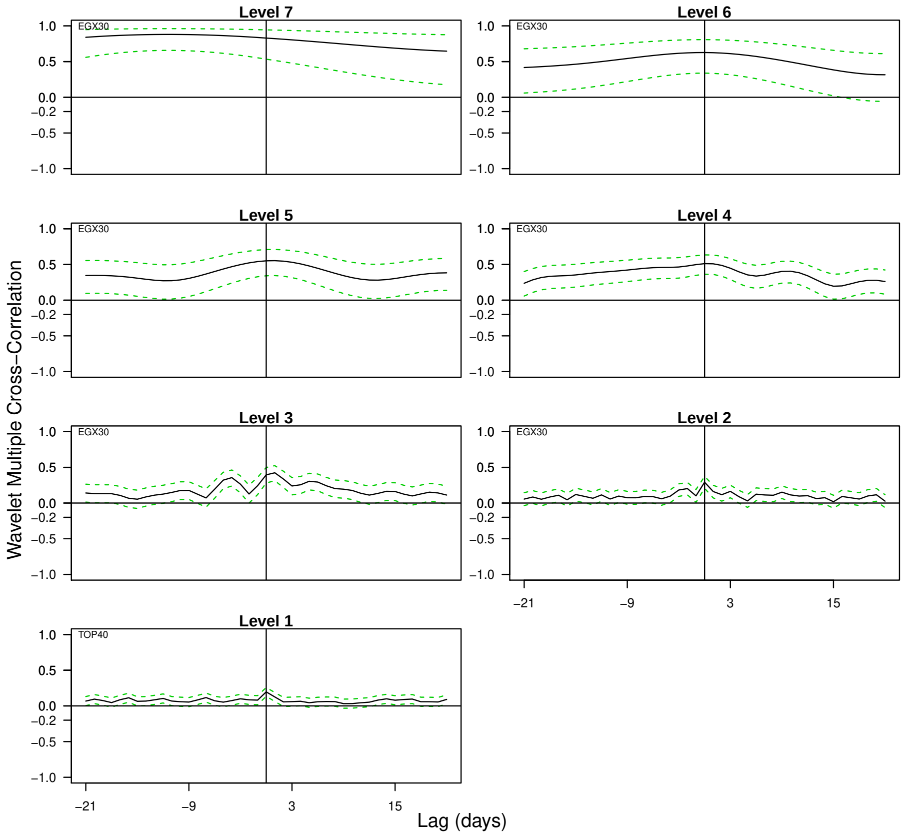

Fig. 2: Wavelet Multiple Cross-Correlation of six major African stock markets returns at different scales.

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

The wavelet multiple cross-correlation also augments in time (Fig. 2). EGX30 (Egypt) maximizes the multiple correlation against a linear combination of the rest of the stock markets returns for all levels (Frequencies) except for the level 1 (High Frequencies) where TOP40 (South Africa) maximizes that. All cross-correlations are not significantly different of zero for all levels and all leads and lags. At level 6, the cross-correlation is clearly significant except for positive lags (leads) between 12 and 22 days. We note a small asymmetry (negative skewness) at level 6 which means that EGX30 (Egypt) has a small tendency to statistically lags other African financial markets at this scale (quarterly to bi-annual).

5. Conclusion

This work applies two wavelet methods proposed by Fernández-Macho (2012), the Wavelet Multiple Correlation (WMC) and the Wavelet Multiple Cross-Correlation

(WMCC) to measure integration between the six largest African financial markets. For the WMC, the results show that the integration between African stock markets is weak in the short and medium run (high and medium frequencies) but tends to rise steadily in the long run (low frequency). This may be a sign of the beginning of integration between African financial markets. Regarding The WMCC, we found that for level 1 (short-term and higher frequency), the TOP40 (South Africa) potentially leads or lags the others stock markets while EGX30 (Egypt) does for the rest except for level 6 (long run) where EGX30 (Egypt) is not a potential leader/follower but indeed lags the others financial markets. The Wavelet Multiple Cross-Correlation confirms results of Wavelet Multiple Correlation since it increases steadily over time.

We can conclude that despite the fact that it grows in time, the integration between the six African financial markets remains weak and offers the possibility of potential gains of diversification. However in the long term in view of the continuous increase in correlation between African stock markets, we can assume the possibility of a near-perfect integration between African stock markets in the coming years which could be an advantage in the development of regional economic policy.

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