Returns Correlation Structure and Volatility Spillovers Among the Major African Stock Markets

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Abstract

The paper analyses the structure of returns comovements and the volatility spillovers among the African stock markets using daily data for the period 2000-2010. We particularly focus on two issues: whether the stock markets of countries with close trading and financial links are more sychronised, and whether the financial crises influences volatility spillovers. Econometric models used include the Factor Analysis (FA), the Vector Autoregressive (VAR) and the GARCH. Our findings suggest that linkages among the African stock markets only exist along regional blocs. South Africa is found to be both the most dominant and most endogenous stock market. Most of the markets exhibit evidence of asymmetry and persistence in volatility. The results also show that it is important to account for structural change in volatility during financial crises when modelling volatility. We outline the investment and policy implications of the findings.

Keywords: Returns and volatility linkages, Factor Analysis (FA), Vector Autoregressive (VAR), Financial Stability, asymmetric GARCH.

JEL Classification: G15, F36

1 Introduction

The past four decades have seen remarkable comovement among world economies. This has been mainly due to the implementation of liberal economic policies across the globe. In Africa, the history of liberal economic policies dates back

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to the 1980s when the International Monetary Fund (IMF) decided to attach economic policy reforms as a pre-condition for financial assistance. These liberal policies were termed Structural Adjustment Programs (SAPs). Proponents of liberal policies argue that these policies have some positive effects on financial and economic development (see Kose, *et al.* 2006). However, opponents of these liberal policies sound alarm over the role of liberalisation in accelerating volatility spillovers, especially during financial crises (Stiglitz, 2002). Consequently, there has been considerable interest by researchers to examine the implication of this emerging wave of liberalisation on transmission of risk across global financial markets. The current study contributes to this debate by examining the returns and volatility linkages among the major African stock markets.

The understanding of returns and volatility linkages is important for a number of reasons. From an investment perspective, returns and volatility spillovers have implications on asset pricing. Thus, understanding them would aid in international portfolio diversification. Furthermore, the knowledge of cross-country volatility transmission is invaluable for institutional investors as it is an important ingredient in formulating hedging strategies (Chinzara and Aziakpono, 2009). The understanding of returns and volatility linkages is also important to policymakers. Policymakers need to pay attention to the sources and consequences of such volatility spillovers if they hope to formulate and appropriately implement regulatory policies that are meant to preserve financial and general macroeconomic stability. International stock market linkages complicate regulation in two main ways. Firstly, if the global regulatory framework is not sychronised, opportunity for regulatory arbitrage is created and consequently investors might try to escape local policies and invest in foreign markets which may have weaker regulatory policies. Secondly, global linkages of financial markets make the regulatory environment quite dynamic. In this regard regulators will need to be proactive in their formulation and implementation of policies. Finally, given that asset prices are an important conduit through which monetary policy impulses are transmitted (Tobin, 1969), it is important for monetary authorities to understand linkages among local and global financial markets when they hope to successfully formulate and implement monetary policy.

Thus far, global linkages of stock markets have drawn considerable empirical attention, albeit African stock markets have not been extensively examined.[1] Lamba and Otchere (2001) use the VAR model to study returns linkages between developed and African stock markets as well as linkages among the African markets for the period 1988 – 2000. They document evidence that weekly returns of South Africa (SA) and Namibia are influenced by those of the US and UK equity markets. They further find significant evidence of linkage of the Ghanaian, Namibian and SA markets to the resource-based stock markets like Australia and Canada. Apart from the fact that they only focus on returns linkages, another possible concern with their study is that they use low frequency data which might be inappropriate given that the stock market normally reacts

[1] For succinctness, we only review studies on Africa. For an extensive review of relevant studies from developed, emerging and other developing stock markets, see Felipe and Diranzo (2005).

to news quickly. Piesse and Hearn (2005) use the exponential GARCH model to analyse volatility linkages among the sub-Saharan African stock markets. Using weekly data between 1997 and 2002, they find that the dominant markets of South Africa and Nigeria transmit volatility, especially to their regional stock markets. Volatility transmission is found to be strong, especially where there are strong trade links. However, this study shares the same problem as that of Lamba and Otchere (2001) with regard to data frequency.

Ogum (2002) uses an asymmetric moving average threshold GARCH (asymmetric-MA-TGARCH) model and daily stock indices for SA, Nigeria and Kenya for the period 1985-1998 to document significant evidence that both conditional mean and conditional variance respond asymmetrically to past innovations. However, using daily data for the period 1999-2003 and focussing only on South Africa and Namibia, Humavindu and Floros (2006) find very low correlation and evidence of neither significant long-run comovement nor volatility spillovers between the two markets. Samouilhan (2006) documents significant evidence of both broad market and sectoral returns and volatility spillovers between UK and SA stock markets for the period 1996-2004. Chinzara and Aziakpono (2009) use daily data for the period 1995-2007 to analyse linkages between the South Africa and the major world stock markets. Using the univariate GARCH and multivariate VAR models, they find evidence of linkages between South Africa and Australia, China and US. They further provide evidence of leverage effects and asymmetry in volatility for all the stock markets as well as limited evidence of risk premium in some of the stock markets.

The current study contributes to the debate on whether African stock markets are sychronised and is related to some of the studies reviewed above. However, we deal with two issues that have not been well addressed by the existing literature on Africa. Firstly, we explore the issue concerning whether African stock markets are sychronised along regional, trade and financial line.[2] Secondly, we explore whether financial crises have implication for structure of linkages among the African markets. There is a reason to believe that financial crises might alter the correlation structure among markets. This reason stems from the fact that investors have the potential to put more weight in their reaction to bad news than good news of the same magnitude (see Li and Hu, 1998, Chinzara, 2010. To account for this possibility, we do this by taking into account the sub-prime financial crisis in our volatility modeling framework. Our decision to focus on the above-mentioned two issues yields dividend in the form of additional findings for the African stock markets.

Firstly, although our findings, consistent with existing literature, suggest that returns and volatility linkages among the African markets are limited, there is new evidence that linkages exist among regional blocs and among some of the big economies. Secondly, we find that there was a general increase in volatility in the African stock markets during the sub-prime crisis. Thus, accounting for

[2] Africa has the following regional and trading blocs Southern African Development Community (SADC), the Common Market of Eastern and Southern Africa (COMESA), Middle East and North Africa (MENA) and the Economic Community of West African States (ECOWAS).

this in the modelling framework turned out to be the appropriate thing to do. Generally, the results suggest that South Africa is both the most dominant and most endogenous stock market. More specifically, on the one hand, it is the one that mostly influences other markets, while on the other hand, it is the one that response the most to events in the other African markets. Finally, as with most studies on financial markets, our findings show that most of the African stock markets exhibit evidence of asymmetry and persistence in volatility.

The remainder of this paper is organised as follows: The next section gives an overview of the sources of stock market linkages. Particularly, we focus on the behavior of trade, capital flows as well as the stock market characteristics during the period of our study. Section 3 describes the methodology and discusses some of the estimation issues. It also the outlines the sources, issues and properties of data. Section 4 presents the empirical results of the study. Section 5 concludes and discusses the policy and investment implications of the findings.

2 Background and sources of stock market linkages

Studies such as Pretorius (2002) argue that *fundamental* linkages among stock markets normally emanate from economic linkages that exist between economies. Here the term *economic linkages* describes the extent to which countries have close investment, trade and any other forms of economic ties. The intuition is that if countries have strong economic ties, a good/bad economic shock in one country will be felt through its effects on, say exporting companies, of the other countries. If these exporting companies are listed on the stock markets then their returns are likely to move in line with the direction of the shock. Consequently, the stock markets of the two countries will commove. However, it is important to note that economic ties do not necessarily have to be between the two countries concerned. It could be that there is a third party country that has strong economic ties with the concerned countries. For instance, if SA and Nigeria have strong trading ties with China, a slowdown in demand for exports by China may simultaneously affect the former economies resulting in comovement between their stock markets. In this regard, industrial structures, (e.g. when countries are heavily dependent on exporting primary commodities), may also increase the chances of fundamental comovement. Broadly speaking, economic linkages occur through trade and international flow of capital.

However, comovement does not always necessarily need to be *fundamental* in nature. It could also be *contagion*, in which case it will not be explained by economic factors. Contagion comovement results from investors taking positions because they think a crisis in one country will eventually affect the others. For instance, if a crisis in the Brazilian stock market results in a general decrease in the appetite for emerging markets stocks irrespective of the economic factors, then this would constitute a *contagion*. Because contagion results from investors rapidly changing their positions, it depends on the market's capacity to satisfy the new positions that investors have taken. Consequently, it depends on factors such as the size and liquidity of the stock market.

In line with the foregoing discussion, this section presents and analyses data on *economic* linkages (trade, financial) and stock market characteristics and highlights the implications for the possibility of integration among the markets. We begin by discussing trade links, followed by financial linkages and finally stock market characteristics.

2.1 South Africa's regional trade links

Figure 1 plots SA exports to the African countries being studied as a ratio of GDP. All countries except Namibia are plotted on the primary scale. The figure shows that between 2000 and 2002, among the countries, Mauritius was the destination of most SA exports. However, since 2002, Nigeria and Kenya have grown to be the main receipts of the bulk of South Africa's exports. Exports to Ghana have also increased. Among the countries, Namibia is the smallest export market. The fact that Kenya and Nigeria have grown to be the some of the main receipts of SA exports implies the possibility that their stock markets are linked to that of SA. On the contrary, the weak export demand from Namibia and Egypt might imply that share prices of SA companies may not be largely affected by slowdown in export demand from these countries. Most of the countries show a slowdown in demand for SA exports during the 2008-2009 the sub-prime financial crisis.

In Figure 2 we plot imports from the African countries to SA as a ratio of GDP. All countries expect for Ghana and Nigeria are plotted on the secondary scale. Most SA imports are from Nigeria followed by Ghana. This suggests that the stock prices of two latter countries are most likely to be affected by an increase or a slowdown in demand for imports by SA. Imports from Kenya and Namibia have shown reasonable growth over the period. Generally, SA demand for imports from most of the African countries slowed down during the sub-prime financial crisis.

2.2 Financial linkages

This section focuses on financial linkages. In the absence of data on the specific flows among the African countries, we focus on aggregate flows. Figure 3 plots the percentage growth in net portfolio equity inflows. It is evident that the growth in net portfolio equity inflows is unstable in all the countries. However, these changes do not exhibit uniformity across countries, except SA and Egypt which show limited signs of uniformity. There are signs that growth in equity flows slowed down for most of the countries during the late 1997-1999 Asian crisis.

Figure 4 plots the percentage growth in net FDI inflows. All countries except for SA are plotted on the primary axis. Generally, growth in net FDI is also unstable. However, unlike equity based flows, the growth in FDI is positive for most of the countries over the period. There are signs of slowdown in growth of FDI for most of the countries, especially between 1998 and 1999. There are also sign of uniformity in the trends of growth in FDI for most countries since 2003.

In Figure 5, we plot growth net debt inflows. Growth in net debt flows is stable between 1996 and 2005. However, Egypt shows a sharp increase from 2005 to 2006, then a sharp decrease thereafter. The exact opposite happens for Nigeria. Mauritius shows a sharp increase between 2006 and 2007.

2.3 Stock market characteristics

In this section we analyse the characteristics, particularly size and liquidity of the African stock markets. Generally, most African stock markets, excluding SA and Egypt are small, illiquid, inefficient and volatile. Piesse and Hearn (2005) attribute this to fact that the markets are in their early stages of development. To examine the size and liquidity of the markets, we use the ratio of stock market capitalisation to GDP and the ratio of stock market turnover to GDP, respectively.

In Figure 6 we plot the trends of stock market capitalisation for the period 2000-2008. It is evident that South Africa is by far the largest stock market in Africa. With the exception of Ghana and Namibia, all the markets show growth in size between 2000 and 2007, albeit SA shows the strongest growth. Kenya and Ghana experienced a decrease in size between 2006 and 2007. Most of the markets show slowdown in capitalisation for the period 2007-2008 due to the financial crisis.

Figure 7 presents trends in turnover ratios for the period 2000-2008. It is evident that SA is the most liquid market followed by Egypt and Morocco. Mauritius, Ghana and Namibia are the most illiquid markets. For all the markets, liquidity has not been stable over the years. SA liquidity shows sharp falls for the 2001-2002. This coincides with the aftermath of the September 11 2001 attacks in the US. Again, most of the markets show slowdown in turnover for the period 2007-2008 due to the financial crisis. If trends in turnover are to go by, then similar trends for Egypt and Morocco could suggest possible comovements of the two markets.

The data presented above suggests possible linkages between the some of the stock markets that are worth further exploring. For instance, the strong trading ties between SA, Nigeria may suggest the possibility of *fundamental* comovement between them. Furthermore, the sudden reductions in net inflows of capital, stock market capitalisation and stock market turnover during the crisis periods suggest that investors generally loose appetite in African stock markets during crises. This might suggest the possibility of *contagion* based linkages among the African markets to a financial crisis, in any of the African countries or elsewhere in the world, is limited. Thus it is worthwhile to further examine the possibility of linkages between the African markets. In this regard, the next section outlines the methods that are used in this study.

3 Data, Methodology and Econometric Procedure

3.1 Data and descriptive statistics

The data used comprise the daily closing indices (P_{it}) for eight African stock markets namely; Egypt, Ghana, Kenya, Mauritius, Morocco, Namibia, Nigeria and South Africa for the period 2000/01/31 to 2010/07/28, totalling 2700 observations. The choice of countries was based on the data availability and on the fact that they are some of the largest in Africa. Following Alagidede (2009), the indices used are in US dollars as this addresses issues with regard to locational inflation, exchange rate risk and other trading costs associated with investing in developing economies. The index of each market is converted into compounded daily returns as follows:

$$y_t = \ln\left(P_t/P_{t-1}\right) \times 100 \tag{1}$$

where y_t is current continuous compounded returns, P_t is the current closing price index and P_{t-1} is the previous day closing stock market index.

An advantage of daily data over low frequency data is that it captures the dynamic interactions that occur within a day, a property that cannot be captured by low frequency data. This is important given that stock markets rapidly react to new information. Secondly, Piesse and Hearn (2005) note that volatility clustering which characterises most financial time series is likely to be distorted if low frequency data, like monthly data, is used. Thirdly, policies that are meant to preserve financial stability are more likely to be effective if they are based on analysing correlations and comovements of high frequency series rather than low frequency data (Berben and Jansen, 2005:835).

However, high frequency data has its own challenges. Two possible challenges regard to dealing with non-trading during holidays and differences in trading times of stock markets. The first problem has been dealt with in two distinct ways in existing literature. Studies such as Sharpe and Kofman (2003) and Glezakos *et al.* (2007) recommend the computation of the relevant missing values using a maximum likelihood simulation approach. On the other hand, studies such as Chowdhury (1994) and Chang, *et al.* (2006) suggest the removal of all the non-traded days across all the markets. In this study, the latter approach is preferred for two main reasons. Firstly, we believe that no method, no matter how good, will simulate the exact data that could have resulted had the market been opened. Secondly, simulation is more valuable if missing data results in small sample problems. This is not a problem here as our sample is very large even after deleting non-trading days. The problem of different trading times in different countries is not a major concern for our study as there is are no large differences in trading times between the markets being studied.

Table 1 reports the summary statistics, namely; sample means, maximums, minimums, medians, standard deviations, skewness, kurtosis, Jarque-Bera (JB) and the Ljung-Box statistics with their p-values for the returns series. The statistics show the characteristics common with most financial data, for example, non-normality in the form of fat tails, excess kurtosis and skewness. Non-normality is also confirmed by statistically significant JB statistics. South Africa, Nigeria, Egypt and Mauritius seem to have quite similar unconditional daily returns averaging 0.040%, 0.040%, 0.038%, and 0.039 respectively. Morocco and Namibia unconditional returns are also in the same range averaging 0.027 and 0.024% respectively. Kenya seems to have outperformed all the other markets with daily returns averaging 0.065%. Ghana is the only market with negative unconditional average returns in the period being studied. Moreover, Ghana has the highest range, quite distinct from other markets. A possible explanation for this is the distortion caused by the revaluation of its currency in July 2007 (Bank of Ghana, 2007).

As evident in Table 1, most of the markets have a high unconditional standard deviation. This is in line with the common observation that emerging and developing markets are risky. Ghana has the highest of 24.84% while Morocco has the lowest of 1.1%. A common observation amongst the four biggest markets on the continent (SA, Egypt, Nigeria and Morocco) is that their stock returns are negatively skewed. All the other markets have distributions which are positively skewed.

The Ljung-Box statistics for both returns and squared returns (i.e. LB(10) and $LB^2(10)$) are statistically significant. The former implies the presence of serial correlation in returns, a contrast to the informational efficiency of the stock market. Methodologically, this justifies the inclusion of the autoregressive term in the mean equation to correct the error term for serial correlation. The latter implies that there is evidence of heteroscedasticity and volatility clustering (i.e. time-varying second moments). This justifies why our study uses of the GARCH family of models, as they capture the time-varying nature of conditional volatility (see Kovaèiæ, 2008:193; Magnus and Fosu, 2006:2044; Mandimika and Chinzara, 2011).

Table 2 reports the pairwise correlation among the returns. It is evident that correlation between most of the stock market returns is very low. In addition, negative correlations are shown in the cases of Ghana and Egypt, Ghana and Namibia, Ghana and SA, Nigeria and Kenya and also between Nigeria and Namibia. This might suggest the existence of international portfolio diversification prospects in the African markets (see Narayan and Smyth, 2005:232). The highest correlation exists between the SA and Namibia. This strong correlation could be because both countries are members of SACU and SADC, and they also have cross-listings agreement. For the other countries, correlations along regional lines seem to be quite low. For instance, correlation between MENA countries (Egypt and Morocco) is only 12%. Correlation is also very low among COMESA members (13% for Kenya and Mauritius) and SADC members (10.5% for Mauritius and Namibia). However, on overall, the pairwise correlation statistics suggest the possibility of linkages between some of the markets. In what follows, we outline the methodology used to examine these possible linkages.

3.2 Methodology and Econometric Procedure

3.2.1 Returns linkages

We analyse returns linkages using the factor analysis (FA) and the vector autoregressive (VAR) models. Following the standard in empirical literature (e.g. Valadkhani *et al.*, 2008), we begin the FA model by specifying the following matrix:[3]

$$\mathbf{r} - \boldsymbol{\mu} = \mathbf{LF} + \boldsymbol{\varepsilon} \tag{2}$$

where $\mathbf{r} = (r_1,r_2,\ldots,r_k)$ denotes the multivariate vector of stock returns, μ =(μ_1, μ_2,..., μ_k) is the corresponding mean vector, $\mathbf{F} = (f_1,f_2,\ldots f_k)$ is the resulting common factor vector, $\mathbf{L} = [\ell_{ij}]_{k\times m}$ is the matrix of factor loadings where $m < \quad k$, ℓ_{ij} denotes the loading of the ith variable on the jth factor and $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2,\ldots,\varepsilon_k)$ is the specific error of r_i. We then run the model and extract factors using the two most widely used approaches, the principal component technique and the maximum likelihood method. Principal Component Analysis (PCA) has the main advantage that it does not require the normality assumption of data and the prior specification of the number of common factors (Valadkhani *et al.*, 2008:167). In order to infer the factor loadings, we use the correlation matrix, since unlike the covariance analysis; it is not sensitive to a change in the units of measurement.

The idea of using the principal component (PC)technique is to reduce the dimensionality of a set of data made up of a large number of variables which have some economic relation to each other, whilst maintaining as much as possible the variation present in the data set (Jolliffe, 2002). This is achieved by transforming "a given set of variables into a new set of composite variables, referred to as principle components (PCs), which are orthogonal to each other" (Figueira *et al.,* 2005:4). According to Nellis (1982:345), given a collection of correlation coefficients for a set of variables, this form of analysis makes it possible to detect whether there exists an underlying pattern of relationships such that it is possible to reduce the data to a set of factors less in number than the set of variables.

Conventionally, the eigenvalue and the cumulative R^2 of the PC are used to establish the explanatory power of each PC (Aziakpono *et al.,* 2007). Accordingly, the current study will follow this approach. The *Kaiser's rule*[4] will also be applied and a cumulative proportion criterion established in order to determine the significance of the eigenvalues of each PC[5]. By following Kaiser's rule (Kaiser, 1960) only statistically significant PCs with variances (eigenvalues) equal to or greater than 1.0 will be retained for analysis (see Nellis, 1982; Meric *et al.,* 2008). This is because these are the PCs that contribute most to

[3] The discussion of the Factor analysis method closely follows Valadkhani *et al.*, 2008.

[4] Kaiser's rule is specifically constructed for use with correlation matrices, although it can also be adapted to suit some covariance matrices (Jolliffe, 2002:114).

[5] It must be noted that although the Kaiser and the cumulative percentage of total variation criteria can be described as ad hoc rules of thumb they have been adopted in this study because they are intuitively plausible and work well in practice (Jolliffe, 2002:112).

the total variance of the variables and are able to describe more of the data than any single variable. On the other hand, the remaining factors (those with eigenvalues less than 1.0) do not need to be retained for analysis as they are likely to be "obscure and more difficult to identify" (Nellis, 1982:346).

In addition to following the Kaiser rule, a cumulative percentage of total variation criteria can be established. According to Jolliffe (2002:113), a reasonable cut-off is usually between 70% and 90%, but this can be higher or lower depending on the practical details of each data set. For instance, a cut-off of more than 90% may be appropriate in cases where although the most obvious and dominant sources of variation can be explained by the first one or two PCs, it is of interest to the researcher to identify the less obvious sources of variation (Jolliffe, 2002:133). Bearing not only the above recommendations in mind, but also the purpose of the current study and the approach followed, instead of imposing a predetermined cut-off level, the explanatory power of the cumulative R^2will rather be used as a guide. For example, in some cases where a PC is not found to be statistically significant according to the Kaiser rule, it may still be considered if it has a fairly large impact on the explanatory power of the cumulative R^2 value.

Alternatively, the maximum likelihood method assumes joint normality of the common factors (or $\mathbf{F}$) and the specific factors (or ε). Under this assumption, $\mathbf{r}$ is multivariate normal with the mean μ and covariance matrix$\sum_r = LL' + \varphi$. Hence, the ML method may be applied to estimate $\mathbf{L}$ and Ψ subject to$L'^{-1}L = \Delta$, which is a diagonal matrix (Valadkhani *et al.*, 2008).

Once the factors are identified, we rotate them using the Varimax rotation method. Rotation ensures that information loadings are not biased toward the early factors. The Varimax method solves this problem by orthogonally rotating the factor axes to maximize the variance of the squared loadings of a factor (column) on all the variables (rows) in a factor matrix. This has the effect of differentiating the original variables by the extracted factor (Garson, 2007:9). Because the Varimax rotation makes each original variable to be associated with one (or a small number) of factors and each factor represents only a small number of variables, the interpretability of the results is simplified (Abdi, 2003). Moreover, the factors can often be interpreted from the opposition of few variables with positive loadings to few variables with negative loadings.

To illustrate the rotation process, consider, $\mathbf{P}$, an $m\times \quad m$ orthogonal matrix with the following relations:

$$\mathbf{LL}' + \mathbf{\Psi} \ = \mathbf{LPP}'L' + \mathbf{\Psi} \ = \ \mathbf{L}^*(\mathbf{L}^*)' + \mathbf{\Psi} \tag{3}$$

and

$$\mathbf{r} - \mu = \ \mathbf{LF} + \varepsilon = \ \mathbf{L} * \mathbf{F} * + \varepsilon \tag{4}$$

in which

$$\mathbf{L}^* = \mathbf{LP} \tag{5}$$

and

$$\mathbf{F}^* = \mathbf{P}'\mathbf{F} \tag{6}$$

Because orthogonal transformation does not change the communalities and the specific variances, it is possible to find an orthogonal matrix, $\mathbf{P}$ that transforms the factor model in such a way that the loadings on the common factors are easier to interpret. In general, this transformation entails rotating the common factors in the m-dimensional space. To specifically illustrate the Varimax method of rotation, let the rotated matrix of factor loadings be $\mathbf{L}^* = [\ell_{ij}^*]$ and the ith communalities c_i^2. $\tilde{\ell}_{ij}^* = \ell_{lj}^* \big/ c_i$ is the rotated coefficients standardised by the (positive) square root of communalities. The varimax rotation involves choosing the orthogonal matrix $\mathbf{P}$ such that the squares of the loadings on each factor are spread out as much as possible. This will in turn facilitate the interpretations of common factors by establishing groups of very large and very small coefficients in any column of the rotated matrix of factor loadings. More formally, this method can be seen as maximizing V, where:

$$V = \frac{\mathbf{1}}{k} \sum_{j=1}^{m} \left[\sum_{i=1}^{k} \left(\tilde{\ell}_{ij}^* \right)^4 - \frac{1}{k} \left(\sum_{i=1}^{k} \tilde{\ell}_{ij}^{*2} \right)^2 \right] \tag{7}$$

The VAR model is able to estimate a dynamic simultaneous equation without placing any prior restrictions on the structure of the relationship as developed by Sims (1980). Since it does not have any structural restrictions, the model allows for the estimation of reduced form of correctly specified equations whose actual economic structure may be not known. This is a vital characteristic in the empirical analysis of data since structural models are usually misspecified.

We specify the VAR model as follows:

$$\mathbf{X_t} = C + \sum_{s=1}^{m} \mathbf{A_s X_{t-s}} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{8}$$

where $\boldsymbol{X}_t$ is a 8×1 column vector of equity market returns for the eight stock markets being studied, C is the deterministic component comprised of a constant, $\boldsymbol{A}_s$ are respectively, 8×1 and 8×8 matrices of coefficients, m is the lag length and ε_t is the 8×1 innovation vector which is uncorrelated with all the past returns $\boldsymbol{X}_s$. The fact that there are many coefficients raises problems in relation to interpretation. Furthermore, some coefficients of a variable may sign across the lags making it difficult to ascertain whether the explanatory variable has a positive or negative effect on the explained variable. As such the VAR model is normally extended by the block exogeneity tests, impulse responses and variance decompositions.

The block exogeneity is a joint test of significance and it separates the variables that are significant from those that do not significantly explain a dependent variable. In the context of this study, we will also use information from the block exogeneity to infer the extent to which the stock markets are exogenous or endogenous. On the other hand, the impulse responses analysis traces the response of the dependent variable to shocks from the explanatory variables in the VAR system (Brooks, 2008:299). More specifically, it seeks to ascertain the time, sign, speed, magnitude and persistence of the response of one markets' returns/volatility to a unit standard error shock in the return/volatility of the other stock markets. The time and persistence of response could be interpreted as a measure of the degree of informational efficiency. Impulse response functions are usually estimated using the generalised impulse response function (GIRF) proposed by Koop, Pesaran and Potter (1996), Pesaran and Shin (1998) and the Cholesky decomposition proposed by Sims (1980). Results obtained from the two techniques are normally very close when shocks are uncorrelated. However, if this is not the case, then the former technique is more appropriate because it is not sensitive to orthogonalisation of variables in the VAR system (Pesaran and Shin, 1998:17). In this regard, we use the generalised technique.

The variance decomposition breaks the variations in one stock market into component shocks in the VAR system. In this way it provides information about the relative importance of innovation of each stock market in describing other stock markets included in the VAR system. More formally, the variance decomposition measures the proportion of the movements in the explained stock market that are as a result of its 'own' innovations, against those from other stock markets.

3.2.2 Volatility and volatility linkages

In Table 1, we presented some evidence that all our returns series are characterised with time-varying volatility. Among others, the GARCH family of models has generally been commended for their ability to capture time-varying volatility. Thus we use the univariate class of these models to analyse volatility of each of the stock markets. Three GARCH models; namely, GARCH, EGARCH and GJR-GARCH were estimated and compared to find the best model for each market. Since most of the models showed that the GJR-GARCH was the most appropriate for most of the markets, this section will only describe this model.[6]

Developed by Zakoian (1990) and Glosten, Jaganathan and Runkle (1993), the GJR-GARCH has the following formulation:

$$r_t = \mu_i + \sum_{i=1}^{k} a_i r_{t-i} + \varepsilon_t \quad , \varepsilon_t / I_{t-i} \sim N\left(0, h_t\right) \tag{9}$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k} + \sum_{i=1}^{q} \beta_i \, h_{t-i}^2 + \varphi \, DUM_{Sub-prme}, \tag{10}$$

$$where\; I_{t-1} \;=\; 1, \;\; if\; \varepsilon_{t-i} \;<\; 0, \; and\; I_{t-1} \;=\; 0, \; if\; otherwise$$

where Equation (9) is an appropriate mean equation whose current innovation ε_t, conditional on a past information set I_{t-i} has a mean of zero, a variance $h_t$and is serially uncorrelated. The terms r_t and r_{t-i} denote the current and lagged returns respectively. Note that we include autoregressive (AR) lags (r_{t-i}) to *whiten* the innovation term since evidence in Table 1 suggested the presence

[6] This is done for succinctness.

of serial correlation.[7] Equation (10) is a TGARCH (p, r, q) variance equation; where h_t is the conditional variance, ω is a constant, α_i is the coefficient of lagged squared residuals (ε_{t-i}^2) is the lagged squared residual from the mean equation and β_i is the coefficient of the lagged conditional variance. $DUM_{Sub-prime}$ is a dummy variable included to account for the effects of the sub-prime financial crisis on conditional volatility. If the coefficient ϕ of the dummy variable is positive and statistically significant, then this implies that volatility significantly increased during the financial crisis. For the equation to be stationary, it is necessary that $\alpha_i + \beta_i < 1$.

I_{t-i} is the asymmetry component and γ_k is its coefficient. In the presence of asymmetry in volatility, γ_k is positive and statistically significant. The intuition is that good news ($\varepsilon_{t-i} \geq 0$) and bad news ($\varepsilon_{t-i}<0$) have different effects on volatility. The effect of good news ($\varepsilon_{t-i} \geq 0$) is measured by α_i, while the impact of bad news ($\varepsilon_{t-i}<0$) is measured of $\alpha_i+ \gamma_k$. Thus if γ_k is positive and statistically significant, it means that bad news has a bigger impact on volatility than good news.

Assuming the conditional normality of residuals, the univariate GARCH models are estimated by maximising the following log-likelihood function:

$$l = -\frac{T}{2}\log\left(2\pi\right) - \frac{1}{2}\sum_{t=1}^{T}\log\left(\sigma_t^2\right) - \frac{1}{2}\sum_{t=1}^{T}\left(r_t - \mu - \phi r_{t-1}\right)^2/\sigma_t^2 \qquad (11)$$

where T is the number of the observations and the other variables are defined as earlier. The Marquardt algorithm will be applied to the non-linear log-likelihood function in order to estimate the parameters. The maximum likelihood requires that initial parameters are set. The software we used (EViews) provides its own initial parameters for the ARCH procedures using OLS regressions for the mean equation. These values could then be altered manually if convergence is not achieved or if parameter estimates are implausible.

4 Empirical Results

4.1 Returns linkages

4.1.1 Factor analysis

In Table 3 we report the Kaiser's Measure of Adequacy (KMA) for both the PCA and ML methods. As evident, the KMA is above the acceptable level of 0.50 in both models. Furthermore, the Bartlett test of sphericity (results not reported) rejected the null hypothesis that the correlation matrix was an identical matrix. However, the KMA statistics are quite low suggesting that the degree of common variance among the eight variables is fairly low.

[7] The number AR lags included in each of the markets depends on whether serial correlation was corrected. The tests for autocorrelation are based on the Durbin-Watson and the Breusch-Godfrey LM Serial Correlation tests.

To gain more insight into the groupings of the markets based on returns comovements, a factor analysis of the correlation matrix was conducted based on both the PCA and the ML approaches. Only four of the resulting eigenvalues were greater than unity based on both methods.[8] For the PC method, the proportions of variance explained by these four factors are 0.20, 0.13, 0.12, 0.11, respectively and cumulatively 0.56. Coincidentally, the proportions of variance and cumulative proportion based on the ML method are very similar to those from the PCA.

In order to facilitate interpretation, the factors obtained from factor analysis of the correlation matrix were rotated using the varimax method. The rotated factors, both from the PCA and ML, are reported in Table 4 and Table 5, respectively. Generally, the results from the two methods are very similar. Based on both methods, the first factor has large weights only for South Africa and Namibia which suggests comovements amongst these markets. This can be explained by the fact that they are both members of SADC and SACU and also the fact that the two stock markets have cross-listings. More evidence of comovement along regional lines can be inferred from the first factor. For instance, the loadings for Egypt and Morocco (MENA region), although low, are in the same region, while the loadings for Nigeria and Ghana (ECOWAS) are both negative. The loadings of the second factor are all very low. However, slim evidence of comovement along regional blocs also seems to emerge. More specifically, Egypt, Morocco, Kenya, and Mauritius have reasonably higher loadings compared to the rest. While the case of Egypt and Morocco has already been explained, the case of Kenya and Mauritius may be due to close trading ties since they are both members of COMESA. In the third factor, the loadings for Egypt, Morocco, Nigeria and SA are all negative. This possible comovement among these markets can be explained by the fact that they are among the largest African economies (World Economic Outlook, 2011). The loadings for the fourth factor are very low although there is slim evidence of comovement between Egypt and Morocco. Also reported in Tables 4 and 5 are the statistics showing the degree of commonality and uniqueness of the different markets. The results suggest that except for Namibia and SA, returns of all the markets are largely unique. This suggests that the African markets are segmented except for SA and Namibia. This result is in line with Biekpe and Collins (2003) and Piesse and Hearn (2005).

4.1.2 VAR results

In order to ensure that the results from factor analysis are robust as well as to gain more insight into the possible comovement suggested by the factor analysis, we experimented with the VAR model. An important initial step in VAR analysis is to select an appropriate lag length. This was initially done using the five information criteria. Since different information criteria normally suggest different lags, we then experimented with different lags starting from the

[8] The eigenvalues, proportion of variance and cumulative proportions are reported on the bottom of Table 4 and 5.

smallest lag selected by the information criteria and increasing the lag while subsequently testing for serial correlation until results with *white noise* residuals were obtained. This approach is similar to that by Gallagher and Taylor (2002) and Chinzara and Aziakpono (2009). The lag that provided results with good diagnostic properties was lag 18. Accordingly, the VAR was estimated using this lag. Given the interpretation-related challenges that are faced when using the VAR model (See the methodology section), the block exogeneity, impulse responses and variance decompositions were subsequently computed to aid interpretation.

The results of the block exogeneity tests are reported in Table 6. They show that Egypt's returns are influenced by those of SA, Morocco and Mauritius. While this result is surprising in the case of Mauritius, it is expected in the case of SA and Morocco. The returns of Ghana are influenced by those of the larger African economies (SA, Egypt and Morocco). The Kenyan returns are significantly influenced by South Africa and Namibia whilst the returns of Mauritius are significantly influenced by those of Egypt, Kenya and South Africa. Morocco is only influenced by Egypt and SA while Nigeria is only influenced by SA. Finally SA is influenced by Egypt, Kenya, Morocco, and Nigeria.

A trend that is evident from the block exogeneity results is that dynamic interactions among the returns seem to be mainly along regional lines and the size of economy. For instance, the countries that seem to influence SA are some of the major African economies and are major African trade partners of SA. This might suggest that linkages are more based on *fundamental* factors rather *contagion* effects. Furthermore the results suggest that SA, with Africa's the largest economy and stock market, seems to explain and to be explained by most of the other markets.

The block exogeneity results, to some extent, complement those obtained from Factor analysis that there are some limited comovements among the African stock returns. Firstly, results from both methods suggest that SA is the most endogenous market. Secondly, both methods suggest that those comovements are along regional blocs. To elaborate on the second point, both methods suggest linkages between SA and Namibia (SACU countries), Egypt and Morocco (MENA countries), and Kenya and Mauritius (COMESA countries). Thirdly, both results suggest linkages among Africa's largest economies (SA, Egypt, Morocco and Nigeria). Nevertheless, in our view, the block exogeneity results are more insightful in the sense that they show which market influences the other whilst the Factor analysis merely highlights that comovement exists between markets.

To examine the sign, speed and persistence of the responses of one stock market to shocks in another stock market, ten-period impulse response functions were estimated using the generalised response approach. The summary of the impulse responses are reported in Figure A1 in the Appendix. Generally, the results show that the response of each of the markets to own innovations starts high and positive, but rapidly drops (in some cases to negative) and eventually dies off.

However, the picture is quite mixed when it comes to responses of different markets to innovations from other foreign markets. With regards to Egypt, responses to innovations from Mauritius and Morocco are the quickest. Response of Egypt to Namibia innovations starts out positive continuing to be slightly significant and dies off at the seventh period. Response of Egypt to innovations from South Africa is more persistent remaining positive and significant until the sixth period. The responses of Egypt to standard error shocks from the remaining markets are quite low and insignificant. With regards to Kenya, we observe that the market seems to respond quickest to innovations in Mauritius, although this response dies off in period two. Responses of Kenya to innovations from the rest of the markets are all low and insignificant. Likewise, Mauritius responds quickest to innovations from Kenya. Although the response of Mauritius's returns to innovations from South Africa, Namibia, Morocco and Egypt are slightly positive, they are all low and insignificant. In the case of Morocco, response is most immediate to innovations from Mauritius, Namibia, South Africa and Egypt respectively, while the responses to innovations from the remaining markets are insignificant. Namibia responds quickest to innovations from Egypt. The response of this market to innovations from South Africa, Morocco and Mauritius are also initially positive, but die off very quickly. The responses of Nigeria and Ghana to innovations from the other markets are low and insignificant. The response of SA returns to innovations from Egypt, Kenya, Mauritius and Morocco is positive but it dies off quickly.

Overall, the response of all the market returns to both own and foreign innovations are quick and die off quickly. Among all the markets, the response of SA seems to be the quickest while those of Ghana and Nigeria seem to be the slowest. The quick response can be interpreted as consistent with informational efficiency of stock markets (see Chinzara and Aziakpono, 2009). Furthermore, the results are in line with those from the block exogeneity and Factor analysis. For instance, all the three results confirm the dominance of SA and that Ghana is most segmented from the rest.

In order to further explore the importance of different markets in explaining the variation of other markets' returns, ten-period variance decompositions were estimated. The results are reported in Table 7. It is evident that except for SA, the proportion of variation explained by own innovations is higher than that explained by innovations from other markets. This suggests that returns comovement are quite limited and is in line with previous studies on the African stock (see Biekpe and Collins, 2003; Piesse and Hearn, 2005; Alagidede, 2009). However, despite this, the results seem to show possible linkages along regional blocs and size of the markets. For instance, SA seems to be the most important in explaining variations in Egypt and Namibia returns, while Namibia seems to be the most important in explaining variations in SA returns. Egypt seems to be the most important in explaining variations in Morocco returns, whilst Kenya seems to be the most important in explaining variations in Mauritius returns. This result is in line with those from factor analysis, block exogeneity and impulse responses. The next section now explores volatility and volatility linkages among the African markets.

4.2 Volatility and volatility transmission across the markets

Firstly, we analysed volatility in each of the markets using the GARCH, EGARCH and GJR-GARCH model. Then the most appropriate model for each market was used to estimate conditional volatility series which were now analysed within a VAR framework to examine the extent of volatility comovement. To estimate the three volatility models, an appropriate mean equation (one with *white noise* residuals) was first estimated. The volatility models were then estimated based on the appropriate models.[9] Table 8 reports the results for the model which was selected for all the markets.

The selection criteria were mainly based on four things. Firstly, we consider the stationarity of the model i.e. $\alpha_i + \beta_i < 1$. Secondly, we look at the ability of the model to capture volatility as indicated by an insignificant ARCH LM statistic. Thirdly, where asymmetry/leverage effects were evident, the comparison is only between the EGARCH and the GJR-GARCH as the standard GARCH model does not capture volatility. Fourth, in cases where models are indistinguishable based on the above three attributes, then the one with the least AIC and SIC is selected.

All the markets showed evidence of asymmetry (see the coefficient in Table 8). This was confirmed by both the EGARCH and the GJR-GARCH models. For this reason, the standard GARCH model was dropped and comparison was done between the two former models. Evidence of asymmetry in stock markets is also documented in other previous studies (see Koutmos and Booth, 1995, Piesse and Hearn 2005, Koulakiotis *et al.*, 2006, Chinzara and Aziakpono, 2009). The coefficient of the dummy variable was positive and significant except for the case of Ghana suggesting that conditional volatility increased during the sub-prime crisis. For most of the markets, except for Nigeria and Morocco, all models were stationary only with one lag (i.e. $\alpha_i + \beta_i < 1$). However, in most cases except for Kenya, Ghana and Mauritius, $\alpha_i + \beta_i$ was very close to one suggesting that volatility is persistent in all the African markets. The models for Nigeria and Morocco showed that volatility was explosive at the first the lag (i.e. $\alpha_1 + \beta_1 > 1$). The finding for Nigeria is in line with that of Emunike (2010). The models for Nigeria only became stationary after the second variance term was added while the models for Morocco became stationary after the second squared lagged error term was added (see Table 8). Both the EGARCH and the GJR-GARCH performed very well in capturing volatility as both had insignificant ARCH LM statistics. However, the GJR-GARCH was more stationary and had lower information criteria across all the markets. Consequently, it was selected as the most appropriate model.

Therefore, based on the GJR-GARCH, the conditional volatility series for each market were estimated. To assess the behaviour of volatility overtime, we

[9] For succinctness and given that the GARCH models have been widely used in many empirical applications, we will not report and discuss the results of all the individual GARCH models estimated. We however discuss the evaluation process taken to determine the most appropriate model and report the results of these most appropriate models.

estimated a simple model where each of the conditional volatility series was regressed with a time variable. Furthermore, we included a dummy variable for the sub-prime crisis to examine whether volatility changed during this period. The results are reported in Table 9. The coefficient for the time variable is positive and significant in all cases except for Mauritius. This suggests that volatility in all markets has generally increased over the period. The opposite can be said for Mauritius. Moreover, except for Ghana and Nigeria, all markets experienced a significant increase in volatility during the sub-prime crisis. The general increase in volatility is expected and is a cause of concern among policymakers as far as financial stability is concerned.

The conditional volatility series were then analysed within a VAR framework in order to examine possible linkages among them. Issues with regard to lag length selection were handled in the same manner as we did in analysing returns linkages. The optimal lag order was lag 16. Based on this lag, the VAR model was estimated and the block exogeneity, impulse responses and variance decompositions were subsequently estimated.

Table 10 reports the block exogeneity results. The results suggest the existence of bidirectional volatility transmission among some of the markets, for instance, between Egypt and SA, Kenya and Mauritius, Morocco and Egypt, SA and Namibia, Morocco and Mauritius, Egypt and Namibia. Generally, volatility in Egypt is significantly affected by SA, Morocco, Mauritius, Kenya and Namibia. South Africa is evidently the most endogenous stock market since its volatility is explained by most of the other markets, except for Nigeria and Ghana. Moreover, SA and Egypt influence volatility in most of the markets, this is expected given that they are the largest markets. Volatilities of Ghana and Kenya are only each significantly influenced by a single market, i.e. Morocco and Mauritius, respectively. However, the most exogenous market is Nigeria since its volatility is not explained by any of the other markets. In overall, volatility linkages seem to be stronger than returns linkages. However, like in the case of returns linkages, results seem to suggest that linkages are strong along regional trading blocs and that bigger markets seem to influence the smaller ones. Furthermore, large markets seem to be more responsive to volatility in foreign markets. This could be attributed to the fact that investors in these markets can quickly respond as they are more liquid.

Figure A2 in the Appendix reports the impulse response functions. Generally, response of volatility to own past standard error shocks is positive and quick for all the markets. Furthermore, except for Ghana and Kenya, this response is persistent. With regards to response of volatility to foreign innovations, it is evident that in the case of Egypt responses to innovations from SA, Morocco and Namibia are positive and persistent, while responses to innovations from the remaining markets is very low and insignificant. Volatility in Kenya only responds to innovations from Mauritius. However, this response is very low and it starts positive then becomes negative and then positive and persistent. Mauritius' volatility seems to respond only to innovations from Egypt, Kenya, Namibia and SA. This response is negative, persistent and quite delayed in all the four cases, but is very insignificant in the case of SA and Namibia. Volatility in Morocco only seems to be responsive to innovations from SA, Egypt and Namibia. While this response is quick and positive, it is very low. Namibia only responds to innovations from SA, Mauritius and Egypt. However, this response is only quick, positive, high and persistent to innovations from SA. The volatility in the SA market only seems to respond to innovations from Namibia, Egypt, Mauritius and Morocco. Except in the case of Mauritius, this response is quick, positive and persistent. The response to innovations from Namibian seems to be the highest and most persistent. Ghana and Nigeria do not seem to respond to innovations from the other African stock markets. This is consistent with the results we reported for variance decompositions.

In overall, the impulse responses results suggest that the volatility in all markets seem to be more responsive to own innovations than innovations from other markets. In cases where markets respond to innovations from other markets, this response seems to be quite delayed but persistent.[10] Furthermore, as is the case with returns, the pattern of response seems be along regional blocs and the size of market and economy.

In order to get more insight into the actual value of each market in explaining volatility of other markets, we estimated the variance decomposition functions. The results are reported in Table 11. As is the case with returns, the results for all the markets show that own past innovations are the most important in explaining the variations in current stock market volatility. However, there is some evidence that out of all the other foreign innovations, innovations from SA are the most important in explaining the variations in Egypt, Morocco and Namibia volatilities. In turn, innovations from Namibia and Egypt also seem to be important in explaining the variations in SA volatility. Moreover, it seems that innovations from Kenya are most important of all in explaining volatility in Mauritius and vice versa. This pattern is also evident in the case of Egypt and Morocco, although it is to a limited extent.

5 Concluding Remarks

The paper analysed whether returns and volatility linkages exist among the major African stock markets. We also analysed the behaviour of volatility in the markets and effects of the sub-prime financial crisis on the long-term trend of volatility. Moreover, we also evaluated the performance of three GARCH-type models in modelling volatilities of the African stock markets. To analyse the structure of correlation among the African stock market returns, we used the FA. In order to further explore the dynamic interactions among the returns, we then used the VAR, block exogeneity, impulse responses and variance decompositions. To analyse volatility, three GARCH-type models were estimated for each of the markets. Using the most appropriate model, conditional volatility series were then estimated for each market and regressed with a time component

[10] However, there are few exceptions where response is quick e.g. the response to SA innovations, where applicable, the response of SA to innovations from Egypt, Morocco and Namibia, the response of Egypt to Morocco innovations, to mention but a few.

and a dummy variable to examine the behaviour of volatility over time and whether volatility was influenced by the sub-prime financial crisis. Moreover, the volatility series were analysed within a VAR framework to examine the dynamic interactions of the stock market volatilities.

In general, the main result shows that there are limited returns and volatility interactions/comovements among the African markets except among close trading partners and large economies. More specifically, results from FA show that patterns of correlation are only evident between/among the following sets of countries: SA and Namibia; Egypt and Morocco; and Kenya and Mauritius; SA, Egypt, Morocco and Nigeria. Generally, this result is also confirmed by the results from VAR, block exogeneity, impulse responses and variance decompositions. The results also show that own innovations are more important in explaining current returns and volatility than foreign innovations. However, in cases where a stock market was found to be responsive to foreign innovations, this response was found to be quick and consistent to the *weak informational efficiency hypothesis.* In general, SA tends to be the most endogenous and dominant market in terms of both returns and volatility influence.

The results from volatility analysis show that the GJR-GARCH is the most appropriate model in analysing volatility in most of the African markets. Volatility of most of the markets was found to be inherently asymmetric and persistent, while volatility is explosive in Nigeria and Morocco. There is evidence to suggest that volatility in most markets significantly increased during the 2008 financial crisis.

These results have implications for both investment and policy. Firstly, limited comovements suggest that opportunity for portfolio diversification exists. Secondly, the fact that volatility and returns are more responsive to domestic innovations than foreign innovations suggests that policymakers should be primarily concerned about stabilising the domestic macroeconomy if they are to maintain financial stability. However, policymakers need to stay vigilant and proactive in the face of international financial crises as volatility tends to increase during these crises. Finally, given the importance of trading-based and regional-based synchronisation among the African markets, diversifying the exports base might be natural macroeconomic strategy that can be employed to hedge against the possibility that harmful volatility that originates from slowdown in demand for certain exports will spillover into domestic stock markets.

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TABLE 1: DESCRIPTIVE STATISTICS

	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
Mean	0.038	-0.001	0.065	0.040	0.027	0.024	0.040	0.040
Median	0.000	0.000	0.000	0.000	0.007	0.000	0.000	0.108
Maximum	9.286	913.324	72.338	16.252	6.256	10.197	38.110	12.889
Minimum	-17.163	-911.052	-68.820	-8.493	-7.699	-9.788	-39.571	-12.852
Std. Dev.	1.854	24.836	2.528	1.172	1.103	1.307	1.609	1.861
Skewness	-0.494	0.017	1.784	3.006	-0.175	0.181	-0.778	-0.293
Kurtosis	8.840	1343.520	463.092	47.651	7.606	11.268	256.455	8.682
Jarque-Bera	3945.88[a]	20200.00[a]	23807.00[a]	2282.30[a]	2399.45[a]	7701.83[a]	7224.00[a]	3669.18[a]
LB(10)	36.781[a]	673.500[a]	195.940[a]	52.306[a]	117.140[a]	20.376[b]	44.753[a]	29.695[a]
$LB^2(10)$	668.58[a]	1275.300[a]	1043.000[a]	690.310[a]	454.810[a]	647.290[a]	913.490[a]	662.880[a]
Adj. Observations	2699	2699	2699	2699	2699	2699	2699	2699

Note: [a] denotes 1% level of significance, [b] 5% level of significance, [c] 10% level of significance.

TABLE 2: CORRELATION MATRIX FOR RETURNS

	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
Egypt	1.000							
Ghana	-0.014	1.000						
Kenya	0.028	0.003	1.000					
Mauritius	0.101	0.004	0.128	1.000				
Morocco	0.120	0.015	0.027	0.105	1.000			
Namibia	0.078	-0.019	0.036	0.105	0.183	1.000		
Nigeria	0.034	0.010	-0.008	0.038	0.027	-0.010	1.000	
SA	0.161	-0.013	0.046	0.092	0.238	0.595	0.004	1.000

TABLE 3: KAISER'S MEASURE OF SAMPLING ADEQUACY

	Principal Components	Maximum Likelihood
Egypt	0.660	0.660
Ghana	0.521	0.521
Kenya	0.575	0.575
Mauritius	0.648	0.648
Morocco	0.759	0.759
Namibia	0.545	0.545
Nigeria	0.530	0.530
SA	0.548	0.548
Kaiser's MSA	**0.573**	**0.573**

TABLE 4: FACTOR ANALYSIS OF CORRELATION MATRIX:

Principal Component Method						
Variable	**Rotated loadings**				**Communality**	**Uniqueness**
	F1	**F2**	**F3**	**F4**		
Egypt	0.168	0.153	-0.085	0.160	0.084	0.916
Ghana	-0.021	0.014	0.023	0.013	0.001	0.999
Kenya	0.050	0.248	0.007	-0.030	0.065	0.935
Mauritius	0.134	0.286	0.046	0.067	0.106	0.894
Morocco	0.288	0.124	-0.054	0.142	0.122	0.878
Namibia	0.683	0.006	0.021	0.018	0.497	0.413
Nigeria	-0.006	0.050	-0.177	0.071	0.039	0.961
SA	0.708	0.037	-0.027	0.038	0.505	0.495
Eigenvalues	1.830	1.137	1.043	1.003		
Proportion of Variance	0.203	0.126	0.116	0.112		
Cumulative Proportion	0.203	0.330	0.446	0.557		

TABLE 5: FACTOR ANALYSIS OF CORRELATION MATRIX

Maximum likelihood method						
Variable	Rotated loadings				Communality	Uniqueness
	F1	F2	F3	F4		
Egypt	0.141	0.090	-0.025	0.356	0.155	0.845
Ghana	-0.020	0.005	0.003	0.009	0.000	1.000
Kenya	0.043	0.126	0.026	0.026	0.019	0.981
Mauritius	0.051	0.199	0.013	0.011	0.126	0.874
Morocco	0.260	0.090	-0.005	0.214	0.121	0.879
Namibia	0.755	0.068	0.017	-0.094	0.583	0.417
Nigeria	-0.008	0.037	-0.061	0.086	0.012	0.988
SA	0.800	0.049	-0.023	0.120	0.657	0.343
Eigenvalues	1.830	1.137	1.043	1.003		
Proportion of Variance	0.203	0.126	0.116	0.112		
Cumulative Proportion	0.203	0.330	0.446	0.557		

TABLE 6: BLOCK EXOGENEITY FOR RETURNS LINKAGES

	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
Egypt		30.68(0.03)	19.14(0.38)	35.66(0.01)	27.77(0.07)	41.09(0.00)	9.74(0.94)	36.40(0.02)
Ghana	20.29(0.32)		1.67(1.00)	8.34(0.97)	13.24(0.78)	11.82(0.86)	2.05(1.00)	5.960(1.00)
Kenya	21.40(0.26)	4.31(1.00)		78.70(0.00)	23.445(0.15)	21.83(0.24)	18.71(0.41)	30.62(0.03)
Mauritius	29.05(0.05)	5.97(1.00)	28.80(0.05)		23.23(0.18)	22.24(0.22)	14.65(0.69)	19.12(0.35)
Morocco	31.93(0.02)	30.52(0.03)	19.95(0.34)	24.08(0.15)		16.85(0.53)	20.37(0.31)	25.94(0.09)
Namibia	14.04(0.73)	12.39(0.83)	26.82(0.08)	15.56(0.62)	18.23(0.44)		15.82 (0.61)	11.17(0.89)
Nigeria	19.37(0.37)	1.82(1.00)	11.07(0.89)	25.10(0.12)	13.34(0.77)	22.08(0.23)		29.81(0.04)
SA	113.92(0.00)	29.74(0.05)	30.98(0.03)	51.44(0.00)	29.764(0.05)	48.95(0.00)	33.15(0.02)	

Note: p-values in parenthesis ( ).

TABLE 7: VARIANCE DECOMPOSITIONS FOR RETURNS LINKAGES

VARIANCE DECOMPOSITION OF EGYPT									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	1.78	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	1.85	92.78	0.09	0.10	0.76	0.47	1.79	0.21	3.79
10	1.88	90.71	0.49	0.55	0.90	0.97	2.11	0.47	3.81
VARIANCE DECOMPOSITION OF GHANA									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	18.49	0.06	99.94	0.00	0.00	0.00	0.00	0.00	0.00
6	25.29	0.13	98.57	0.09	0.12	0.42	0.04	0.03	0.60
10	25.35	0.18	98.10	0.10	0.12	0.58	0.17	0.03	0.71
VARIANCE DECOMPOSITION OF KENYA									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	2.43	0.01	0.00	99.99	0.00	0.00	0.00	0.00	0.00
6	2.57	0.61	0.02	97.35	0.44	0.37	0.50	0.13	0.60
10	2.58	0.73	0.02	96.53	0.48	0.51	0.68	0.17	0.88
VARIANCE DECOMPOSITION OF MAURITIUS									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	1.14	0.49	0.00	1.73	97.78	0.00	0.00	0.00	0.00
6	1.17	1.33	0.01	3.44	92.52	0.39	0.70	0.04	1.57
10	1.19	1.68	0.01	3.79	90.72	0.62	1.21	0.10	1.88
VARIANCE DECOMPOSITION OF MOROCCO									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	1.08	1.02	0.13	0.14	0.62	98.09	0.00	0.00	0.00
6	1.11	1.23	0.21	0.82	0.70	96.32	0.37	0.29	0.07
10	1.11	1.27	0.29	0.84	1.00	95.42	0.58	0.38	0.22
VARIANCE DECOMPOSITION OF NAMIBIA									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	1.30	0.68	0.00	0.13	0.95	0.00	95.82	0.00	2.41
6	1.32	1.33	0.09	0.41	1.45	0.14	93.74	0.31	2.52
10	1.32	1.47	0.16	0.54	1.67	0.20	92.88	0.43	2.66
VARIANCE DECOMPOSITION OF NIGERIA									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	1.60	0.06	0.02	0.07	0.03	0.04	0.03	99.76	0.00
6	1.61	0.14	0.04	0.19	0.12	0.30	0.30	98.85	0.06
10	1.63	0.23	0.05	0.59	0.30	0.80	0.72	96.98	0.34
VARIANCE DECOMPOSITION OF SOUTH AFRICA									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	1.85	2.82	0.00	0.29	0.61	4.01	30.15	0.00	62.12
6	1.87	3.00	0.06	0.79	1.36	4.18	29.62	0.05	60.95
10	1.88	3.15	0.13	0.98	1.48	4.37	29.44	0.09	60.36

TABLE 8: THE SELECTED MODEL: GJR-GARCH

	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
ω	0.04a	380.59a	3.40a	1.05a	0.03a	0.05a	0.04a	0.09a
α1	0.04a	0.01a	0.11a	0.01a	0.19a	0.01	0.33a	0.01
β1	0.94a	0.46a	0.48a	0.47a	0.91a	0.94a	1.18a	0.88a
α2	n/a	n/a	n/a	n/a	-0.14a	n/a	n/a	n/a
β2	n/a	n/a	n/a	n/a	n/a	n/a	-0.36a	n/a
$\alpha_i + \beta_i$	**0.98**	**0.47**	**0.59**	**0.48**	**0.96**	**0.95**	**0.98**	**0.89**
γ	0.01b	0.10a	-0.13a	0.09a	0.03a	0.05a	-0.18a	0.14a
Dum	0.04a	-379.81a	4.59a	0.54a	0.02a	0.03a	0.61b	0.14a
F-LM	**0.32**	**0.23**	**0.81**	**1.97**	**0.08**	**0.1**	**1.6**	**0.04**
LL	-5317.5	-10663.3	-5895.21	-4278.93	-3796	-4417	-4032	-5003.
AIC	**3.95**	**7.92**	**4.38**	**3.18**	**2.82**	**3.28**	**3.01**	**3.71**
SIC	**3.96**	**7.94**	**4.39**	**3.19**	**2.84**	**3.29**	**3.03**	**3.73**

TABLE 9: VOLATILITY OVER TIME

STOCK MARKET	β1	β2
Egypt	2.816(0.000)[a]	0.000511(0.000)[a]
Ghana	53.753(0.078)[c]	-0.038167(0.845)
Kenya	5.157(0.000)[a]	0.002734(0.000)[a]
Mauritius	-0.204(0.000)[a]	0.001158(0.000)[a]
Morocco	0.660(0.000)[a]	0.000393(0.000)[a]
Namibia	1.449(0.000)[a]	0.000168(0.000)[a]
Nigeria	5.455(0.001)[a]	-0.000895(0.406)
SA	0.908(0.000)[a]	0.001806(0.000)[a]

Notes: [a] denotes significance at 1% level, [b] significance at 5% level, [c] significance at 10% level.

TABLE 10: BLOCK EXOGENEITY FOR VOLATILITY LINKAGES

	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
Egypt		9.17(0.91)	14.28(0.58)	107.81(0.00)	70.44(0.00)	150.51(0.00)	1.74(1.00)	200.65(0.00)
Ghana	14.87(0.53)		0.27(1.00)	1.55(1.00)	2.01(1.00)	0.82(1.00)	0.02(1.00)	1.81(1.00)
Kenya	32.17(0.01	0.36(1.00)		520.08(0.00)	15.99(0.45)	11.58(0.77)	0.21(1.00)	42.74(0.00)
Mauritius	67.42(0.00)	1.00(1.00)	226.45(0.00)		48.25(0.00)	38.67(0.00)	0.96(1.00)	74.48(0.00)
Morocco	115.00(0.00)	25.57(0.06)	22.17(0.14)	28.40(0.03)		18.14(0.32)	2.09(1.00)	74.62(0.00)
Namibia	26.80(0.04)	1.72(1.00)	1.31(1.00)	9.11(0.91)	25.42(0.06)		5.85(0.99)	46.14(0.00)
Nigeria	2.64(1.00)	0.02(1.00)	0.04(1.00)	0.29(1.00)	1.14(1.00)	1.03(1.03)		0.45(1.00)
SA	324.24(0.00)	1.72(1.00)	19.00(0.27)	71.54(0.00)	91.32(0.00)	75.94(0.00)	2.26(1.00)	

Note: P-values in brackets ( ).

TABLE 11: VARIANCE DECOMPOSITIONS FOR VOLATILITY LINKAGES

VARIANCE DECOMPOSITION OF EGYPT:									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	0.40	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	1.02	88.27	0.04	0.01	0.07	0.82	0.89	0.02	9.86
10	1.27	79.04	0.09	0.12	0.13	1.46	1.53	0.01	17.62
VARIANCE DECOMPOSITION OF GHANA:									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	8055.74	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
6	8085.65	0.04	99.29	0.00	0.01	0.66	0.00	0.00	0.01
10	8087.85	0.05	99.23	0.00	0.01	0.68	0.01	0.00	0.01
VARIANCE DECOMPOSITION OF KENYA:									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	11.55	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00
6	12.80	0.03	0.01	96.46	3.19	0.28	0.03	0.00	0.01
10	12.92	0.08	0.01	94.88	4.38	0.52	0.05	0.00	0.08
VARIANCE DECOMPOSITION OF MAURITIUS:									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	0.05	0.00	0.00	0.14	99.86	0.00	0.00	0.00	0.00
6	0.14	2.81	0.00	2.77	94.02	0.16	0.05	0.00	0.18
10	0.20	4.73	0.01	6.04	88.46	0.17	0.04	0.00	0.56
VARIANCE DECOMPOSITION OF MOROCCO:									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	0.57	0.16	0.00	0.00	0.07	99.77	0.00	0.00	0.00
6	0.71	1.01	0.02	0.05	0.25	96.35	0.48	0.00	1.83
10	0.77	1.05	0.05	0.24	0.41	94.22	0.91	0.01	3.11
VARIANCE DECOMPOSITION OF NAMIBIA:									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	0.17	0.06	0.00	0.00	0.52	0.00	99.42	0.00	0.00
6	0.41	0.27	0.00	0.02	1.00	0.08	97.82	0.00	0.79
10	0.52	1.42	0.01	0.02	1.10	0.11	92.89	0.00	4.45
VARIANCE DECOMPOSITION OF NIGERIA:									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	11.68	0.01	0.00	0.00	0.00	0.01	0.00	99.98	0.00
6	43.61	0.03	0.00	0.00	0.00	0.02	0.02	99.92	0.00
10	44.42	0.09	0.00	0.01	0.01	0.02	0.04	99.82	0.01
VARIANCE DECOMPOSITION OF SA:									
Period	S.E.	Egypt	Ghana	Kenya	Mauritius	Morocco	Namibia	Nigeria	SA
1	0.92	0.45	0.01	0.04	0.00	0.20	15.46	0.00	83.84
6	1.99	0.44	0.00	0.25	0.65	0.57	14.01	0.00	84.07
10	2.60	3.24	0.01	0.15	0.99	1.74	12.19	0.00	81.68

Figure 1: Ratio of SA's Export to Africa countries to GDP

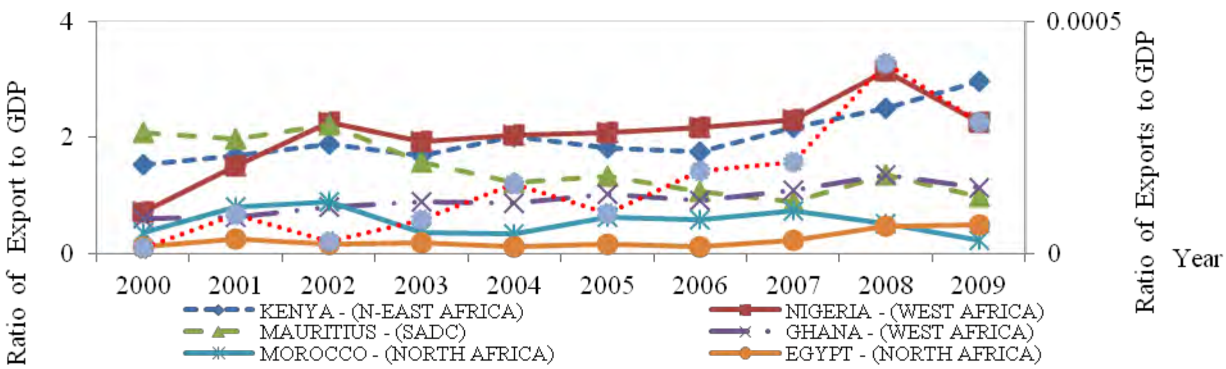

Figure 2: SA's Import Regional Trade (Million USD)

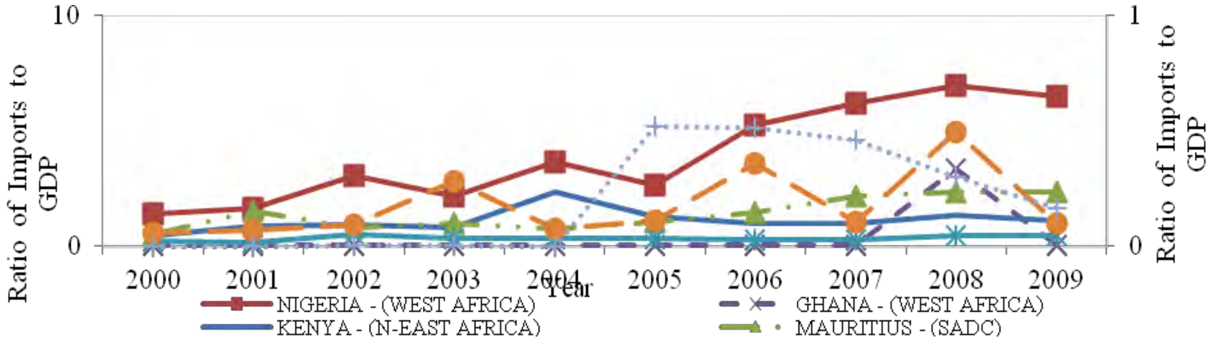

Figure 3: Net Portfolio Equity Inflows (Million USD)

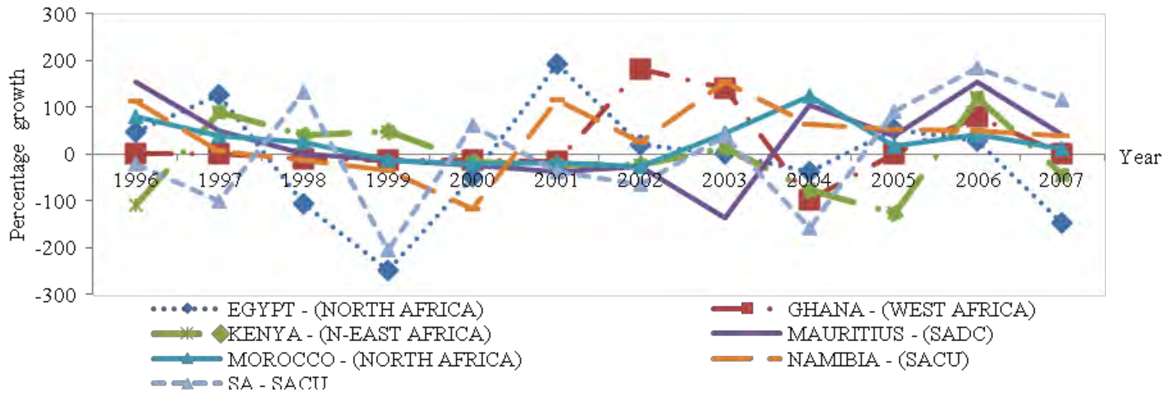

Figure 4: Percentage Growth in Net FDI Inflows (Million USD)

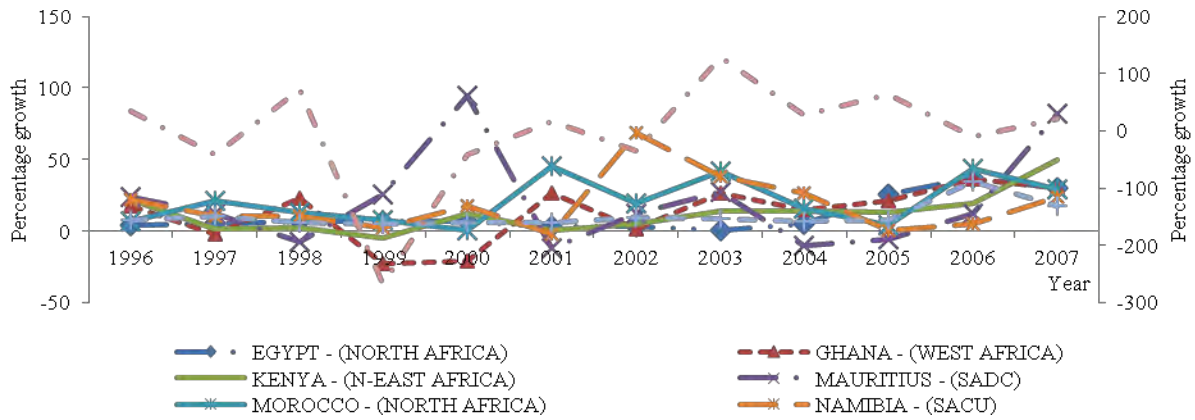

Figure 5: Percentage Growth in Net Debt Inflows (Million USD)

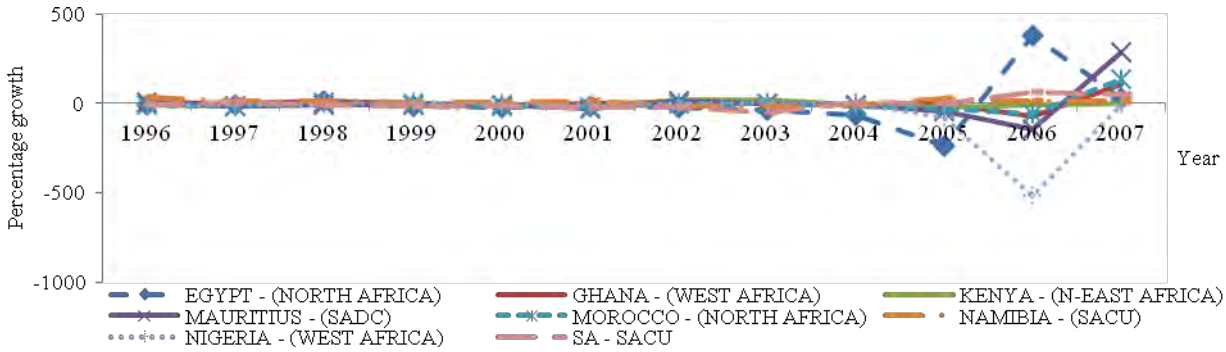

Figure 6: Stock market capitalisation as % of GDP

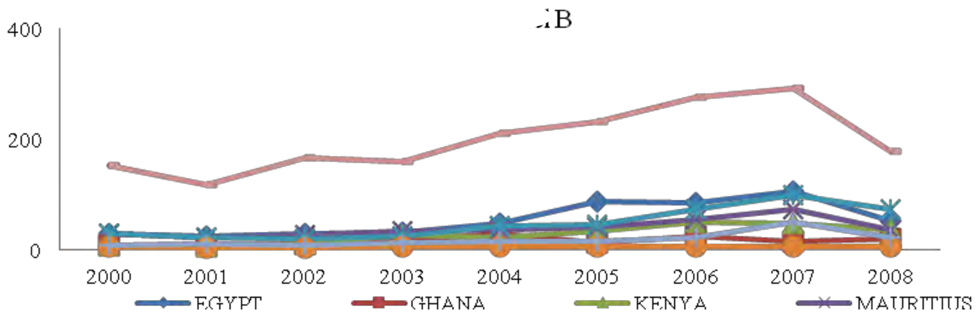

Figure 7: Stock market turnover as % of GDP

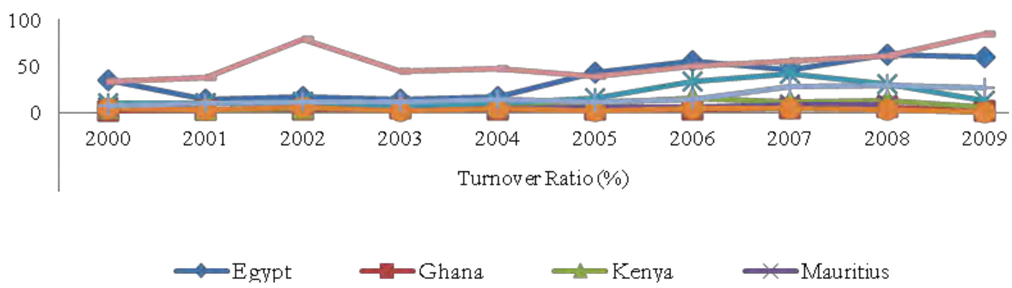

Figure A1: Impulse Responses for Returns Linkages

Figure A2: Impulse responses for volatility linkages