How are Africa's emerging stock markets related to advanced markets? Evidence from copulas

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Abstract

This paper examines the dependence structure between two developed and four emerging African stock markets in a copula framework. Using daily data from January 2000 to April 2014, our empirical results show that dependence structure between African and international stocks varies overtime, but generally weak. There is asymmetric and weak tail dependence for all the countries, implying stock return co-movement varies in bearish and bullish markets and that the dependence is generally not strong in extreme market conditions. We also find that extreme downward stock price movements in the advanced markets do not have significant spillover effects on Africa's emerging stock markets.

1 Introduction

The nature of dependence across stock returns plays a crucial role in asset pricing, portfolio allocation and policy formulation. Investment practitioners pay close attention to the co-movement between equity markets, as a proper grasp of its nature and measurement affects the risk-return trade-off from international diversification; typically, international portfolio diversification becomes less effective when markets are in turmoil. Policy makers, on the other hand, are more interested in how strong linkage across stock markets influences the transmission of shocks, its consequences as well as implications for risk management.

There is vast literature on the dependence between international stock markets, mainly spurred by the seminal contribution of Grubel (1968) who alluded to the fact that investors could obtain welfare gains by diversifying their portfolio internationally, where the gains hinges primarily on the correlation between stocks. Linear correlation has been used as the canonical measure of association between stocks due to its convenient properties (see Embrechts, McNeil, &

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Straumann, 2002). Early works in this area were based on models that jointly price stocks under the assumption of constant correlation (Agmon, 1972; Solnik, 1974). Subsequent contributions present evidence that stock return comovement varies with time (Brooks and Del Negro, 2004; Forbes & Rigobon, 2002; Kizys & Pierdzioch, 2009). Owing to the drawbacks of linear correlation, multivariate GARCH models have become the typical approach of modelling time-varying stock dependence and there is exponential growth of research in this area (see Syllignakis & Kouretas, 2011; Gjika & Horvath, 2013; Baumöhl & Lyócsa, 2014; Kundu & Sarkar, 2016). However, one major limitation of the multivariate GARCH approach is the assumption that return innovations are characterized by a symmetric multivariate normal or Student-t distribution (Patton, 2006b; Garcia & Tsafack, 2011). Evidently, this assumption seems to be at odds with the empirics; the distribution of financial returns possesses heavy tails than those of the normal distribution and dependence between stocks returns are usually nonlinear and asymmetric (Embrechts, McNeil, & Straumann, 2002).

Against this background, researchers have resorted to a relatively new approach, copula, to model the dependence between stock returns. Copulas are functions that join multivariate distributions to their one-dimensional margins (Sklar, 1959). There are several advantages in using copula models. First, copula-based models provides much flexibility in modelling multivariate distributions by making it possible to fit models for the marginal distributions separately from the dependence structure (copula) that connects them to form a joint distribution (Patton, 2012). Second, copula functions allow us to model dependence in extreme market conditions and they signify both the degree and structure of the dependence. Third, unlike linear correlation, copula functions are invariant to non-linear strictly increasing transformations of the data (Embrechts, McNeil, & Straumann, 2002). For example, the dependence between X and Y will be the same as the dependence between $\ln(X)$ and $\ln(Y)$.Thus, copula functions provide a realistic description of the dependence in financial assets.

There is abundant empirical literature on the dependence structure among international stock returns using copulas. For example, Yang, Cai, Li and Hamori (2015) investigates the dependence structure among international stock markets using hierarchical Archimedean copulas and finds strong dependence between Emerging and European stock markets, weak dependence between Frontier and other markets, and evidence of contagion during the global and the EU debt crisis. Similarly, using static copulas, Basher, Nechi and Zhu (2014) studies the dependence pattern across GCC stock returns and concludes that dependence is asymmetric. Bhatti and Nguyen (2012) uses conditional extreme value theory and time-varying copula to capture the tail dependence between the Australian financial market and other selected international stock markets and finds evidence of tail dependence. Mensah and Premaratne (2014) also examine the dependence structure among banking sector stocks from 12 Asian markets using static and time-varying copulas and uncovers evidence of asymmetric dependence. These studies are mainly focused on international markets, other than those from Africa.

Although studies abound, there is no empirical evidence on the dependence structure of African stock markets with other international stock markets. Only a smattering of papers has focused on the comovement of Africa's emerging stock markets with other international markets, despite the region's growing importance in the global economy. It is also instructive to note that the few existing empirical studies on Africa (Adjasi & Biekpe, 2006; Alagidede, 2009; Alagidede & Panagiotidis, 2011) focus on comovement using cointegration techniques, which has major weaknesses. For instance, it requires long span of data, which many of the equity markets in Africa, with the exception of a few, do not have, thus rendering a number of the previous studies questionable. Moreover, using linear dependence measures is at odds with the widely acknowledged fact that return distributions are non-normal. It is therefore essential to assess the dependence between African stock markets and other international markets with more accurate measures of dependence.

The contribution of this paper is twofold. Firstly, to the best of our knowledge, this is the first study that applies copula models to investigate the time-varying dependence pattern between international and African stock returns. We characterize the bivariate dependence structure between African and other international stock returns through copulas. To model the dynamic dependence, we use the Generalized Autoregressve Score (GAS) model proposed by Creal, Koopman and Lucas (2013), which uses the standardized score of the copula log-likelihood function to update parameters over time. The GAS model performs well in capturing different types of dynamics compared to the lagged and autoregressive specification in Patton (2006) and the DCC specification in Christoffersen, Errunza, Jacobs, and Langlois (2012) and Christoffersen and Langlois (2013). Thus, our study provides new insight on the dependence structure of African stocks in African markets.

Secondly, this study is novel as it investigates African stock market quantiles conditional on advanced stock price movements, with the aim of uncovering shock spillovers. In this respect, a few studies have applied copula and quantile models in order to capture shock spillovers. For example, Sim and Zhou (2015) used a quantile-on-quantile regression to characterize the effect of oil price shock quantiles on US stock return quantiles. Subsequently, Reboredo and Ugolini (2016) used a copula-based approach to investigate the impact of quantile and interquantile oil price movements on different stock return quantiles for a broad set of global indices. They compute unconditional and conditional quantile stock return quantiles based on marginal models for stock returns and copula function for oil-stock dependence and proof the effectiveness of this approach. In line with Reboredo and Ugolini (2016), we capture the dependence structure between stock returns and compute conditional quantile through copulas.

The empirical results show that dependence structure between African and international stocks varies overtime, but generally weak. Further, we find evidence of asymmetric and weak tail dependence for all the countries. This implies that the stock return comovement varies in bearish and bullish markets and that the dependence is generally not strong in extreme market conditions. Further, we find that that extreme downward stock price movements in the US and UK do not have significant spillover effects on Africa's emerging stock markets.

The remainder of this paper proceeds as follows. Section 2 presents a brief discussion of copula theory. Section 3 highlights the empirical application of copula models, and Section 4 presents the data. Section 5 shows the empirical results and Section 5 concludes.

2 Copula Theory

Sklar (1959) theorem allows us to decompose any multivariate into univariate marginal distributions and a copula, which fully captures their dependence. More formally, we define a continuous n-variate cumulative distribution function as $F(x_{1,\ldots}x_n)$. Its univariate margins are $F_i(x_i)$, $i = 1, \ldots, n$ where $F_i(x_i) = F(\infty, \ldots, x_i, \ldots, \infty)$.Given these conditions, Sklar (1959) showed that there exists a function C, known as a *copula,* that maps $[0,1]^n$ into [0,1] such that

$$F_n(x_{1,\ldots}x_n), = C[F_1(x_1), \ldots, F_n(x_n)]. \tag{1}$$

Differentiating Equation (1) once with respect to all its arguments, we obtain the joint density function. It is the product of the copula density and the n marginal densities,

$$\frac{\partial^n F(x_1, \ldots, x_n)}{\partial x_1, \ldots, \partial x_n} = \Pi_{i=1}^n f_i(x_i) \frac{\partial^n C[F_1(x_1), \ldots, F_n(x_n)]}{\partial F_1(x_{1),\ldots,} \partial F_n(x_{n)}}. \tag{2}$$

Further, if we define $u_i = F_i(x_i)\tilde{}U[0,1]$, $i = 1, \ldots, n$ as the probability integral transformation (PIT) variables of the marginal models, then the unconditional copula is defined as the multivariate distribution with uniform [0,1] margins,

$$C(u_i, \ldots, u_n) = [F_n(F_1^{-1}(u_i), \ldots, F_n^{-1}(u_n)); p_F] \tag{3}$$

Equation (3) states that, given the marginal distributions u_i to u_n, there exists a copula function that maps the univariate margins u_i to u_n via F^{-1}; and the joint of the (abscise values) $F^{-1}(u_i)$ to a single, n-variate function $F_n(F_1^{-1}(u_i), \ldots, F_n^{-1}(u_n))$ with the same correlation structure as p_F (Meissner, 2014). Thus, given n random variables with marginal distributions that are uniform on the interval from zero to one, copulas provide an easy mapping from the univariate marginal distributions to their $n-$variate distribution, supported on $[0,1]^n$. This method of transforming an $n-$dimensional function on the interval [0,1] into a unit-dimensional function applies irrespective of the degree of dependence among the random variables (Heinen & Valdesogo, 2012).

There are several advantages of using copula functions in finance. First, they provide a flexible way of modelling nonlinear dependence. Unlike correlation, we can specify different distributions for the margins and still be able to model their joint dependence with any copula of choice. Secondly, copulas are able to capture the exact comovement between two or more random variables, irrespective of their scale of measure; the marginal determine the scaling and shape. In other words, the tail dependence between the random variables is invariant under strictly increasing transforms. An account of unconditional copulas can be found in Cherubini Luciano and Vecchiato (2004), Nelsen (2007).

3 Empirical Methods

3.1 *Marginal Models*

Prior to fitting the bivariate copula models, we specify appropriate models for the conditional (marginal) densities (conditional means, variances and distributions). Financial time series exhibit some well-documented characteristics such as long-memory, fat-tails, and conditional heteroscedasticity. Thus, it suffices to apply autoregressive-moving average (ARMA(p,q)) models to the conditional means (where p is the order of the autoregressive part and q is the order to the moving average part) as well as generalized autoregressive conditional heteroskedasticity (GARCH(p,q)) models to the conditional variances (where p and q are the order of the GARCH and ARCH terms, respectively) as follows:

$$Y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{4}$$

$$\varepsilon_t = \sigma_t^2 z_t, z_t \sim NIID(0,1) \tag{5}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{6}$$

where Y_t is the log-difference of stock market price at time t; c is the constant term in the mean equation; ε_t is the real-valued discrete time stochastic process at time t; z_t is an unobservable random variable belonging to an i.i.d. process; σ_t^2 is the conditional variance of ε_t; ω, α_i and β_i are the constant, ARCH parameter, and GARCH parameters respectively. In the case of GARCH (1,1) model, the following inequality restrictions must be satisfied to ensure that the model is rightly specified: (i) $\omega \geq 0$, (ii)$\alpha_1 \geq 0$, (iii) $\beta_1 \geq 0$ and (iv) $\alpha_1 + \beta_1 < 1$. When $\alpha_1 + \beta_1 = 1$ then the conditional variance will not converge on a constant unconditional variance in the long run (Bollerslev, 1986). We estimate the GARCH models by maximum likelihood.

3.2 *Copula Models*

Equation (1) outlined the copula distribution for $n$number of assets. In the case of a bivariate joint distribution, with marginal, $F_X(x)$ and $F_Y(y)$, we can express the distribution as

$$F_{X,Y}(x,y) = C(F_X(x), F_Y(y)) \tag{7}$$

An important observation from Equation (7) is that the joint distribution is separated into marginal parts and dependence structure (copula) without losing any information. Moreover, we can assume different distribution families for each of the marginal, $F_X(x)$ and $F_Y(y)$. One key feature of copula functions is that the tail dependence between two random variables, X and Y, is invariant under strictly increasing transformation of X and Y. For example, the dependence between X and Y will be the same as the dependence between $\ln(X)$and $\ln(X)$. Following previous studies (Patton, 2012), we can define the lower and upper tail dependence between X and Y as

$$\tau^L \lim_{u\to 0} \Pr\{F_Y(Y) \leq u | F_X(X) \leq u\} = \lim_{u\to 0} \frac{C(u,u)}{u} \tag{8}$$

$$\tau^U \lim_{u\to 1} \Pr\{F_Y(Y) \geq u | F_X(X) \geq u\} = \lim_{u\to 1} \frac{1-2u+C(u,u)}{1-u} \tag{9}$$

where τ^L and $\tau^U \in (0,1)$. If the above limits exist and if τ^L and $\tau^U > 0$, X and Y tend to be left (lower) or right (upper) tail dependent. The tail dependence captures the behavior of the random variables during extreme events. Given two stock market returns, X and Y, tail dependence measures the probability that we will observe an extremely large fall (rise) of stock market X given that the stock market Y has experienced an extreme fall (rise). Informally, the tail dependence determines whether the two markets crash or boom together; investors holding long portfolios are mainly concerned with the downward movement, whereas the risk of large upward movement is the concern of investors holding short positions.

We estimate Equation (7) for different copula specifications in order to capture different patterns of tail dependence. Table 1 shows the functional forms for four copulas, namely: Gaussian (Normal), Student's t, Gumbel, and rotated Gumbel copulas. The Gaussian copula is the most widely used in finance due to its convenient properties. However, it is unable to capture tail dependence. The Student's t copula on the other hand assumes symmetric dependence for both lower and upper tails of the joint distribution. The rotated Gumbel are useful only when examining dependence during market crashes; conversely, the Gumbel copula is able to capture only upper tail dependence, thus making it useful during periods of market boom.

3.3 *Generalized Autoregressive Score (GAS) model*

The time-varying copulas are estimated based on the Generalized Autoregressive Score (GAS) model of Creal, Koopman and Lucas (2013). We assume the copula parameter evolves as a function of its own lagged value and a "forcing variable" related to the scaled score of the copula log-likelihood. This approach uses strictly increasing transformation (e.g. log) to copula parameters in order to ensure that parameters are constrained to lie in a particular range (e.g $\rho \in (-1,1)$). Following Patton (2012), the evolution of the transformed parameter is denoted

$$f_t = h(\delta_t) \Leftrightarrow \delta_t \Leftrightarrow h^{-1}(f_t) \tag{10}$$

where

$$f_{t+1} = \theta + \beta f_t + \alpha I_t^{-1/2} s_t \tag{11}$$

$$s_t \equiv \frac{\partial}{\partial \rho} \log c(u_t, v_t; \delta_t) \tag{12}$$

$$I_t \equiv E_{t-1}\left[s_t s_t'\right] = I(\delta_t) \tag{13}$$

By these expressions, the future value of the copula parameter dependence on a constant, the present value, and the score of the copula log-likelihood $I_t^{-1/2} s_t$. We apply the GAS model to the time-varying Gaussian, Gumbel and rotated Gumbel copulas.[1] We us $\delta_t = (1 - \exp\{-f_t\}) / (1 + \exp\{f_t\})$ to ensure that the Gaussian copula parameter lie in (-1, 1). We use the function $\delta_t = 1 + \exp(f_t)$to ensure that the Gumbel and rotated copula parameter is greater than one.

We can estimate the copula parameters using two alternative frameworks: Maximum Likelihood Estimation (MLE) method and the Inference functions for the Margins (IFM). We estimate the copulas in this study by the latter method due to its advantages over the MLE. First, unlike the MLE, the IFM requires few computations; second, it is highly efficient; thirdly, the goodness of the margins can be assessed separately from that of the copula; lastly, the series of random variables are not required to be of equal length (Bhatti and Nguyen, 2012).

3.4 *Advanced stock return quantile effects on African stock return quantiles*

Apart from the dependence structure, we also examine whether extreme price movements in the advanced stock markets have any spillover on African stocks. In this regard, we examine the impact of lower quantile advanced stock price movements on African stock price quantile. In line with Reboredo and Ugolini (2016), the α-quantile of stock return distribution at time t given by $p(y_t \leq q_{\alpha,t}^{y_t}) = \alpha$ can be computed as

$$q_{\alpha,t}^{y_t} = F_{y_t}^{-1}(\alpha) \tag{14}$$

where y_t is the stock return, $F_{y_t}^{-1}(\alpha)$ is the inverse of the distribution function of y_t. The α-quantile for low values of alpha is typically referred to as value-at-risk (VaR). Furthermore, we can obtain the conditional $\alpha-$ quantile of African stock return distribution at time t for a given β-quantile of advanced market stock return given by $p(y_t \leq q_{\alpha,\beta,t}^{y_t|x_t}) = \alpha$ as:

$$q_{\alpha,\beta,t}^{y_t|x_t} = F_{y_t|x_t \leq q_{\beta,t}^{x_t}}^{-1}(\alpha) \tag{15}$$

[1] For the student-t copulas, we considered the ARMA(1,q)-type process Patton (2006) for the linear dependence parameter as follows $\rho_t = \Lambda_1\left(\psi_0 + \psi_1 \rho_{t-1} + \psi_2 \frac{1}{q} \sum_{j=1}^{q} t_v^{-1}(u_{t-j}) . t_v^{-1}(v_{t-j})\right)$ Where $\Lambda_1 = (1 - e^{-x})(1 + e^{-x})^{-1}$ is modified logistic transformation that which forces the value of within the interval (-1,1).

where $F^{-1}_{y_t|x_t \leq q^{x_t}_{\beta,t}}(\alpha)$ denotes the inverse distribution of y_t conditional on .

Given the conditional mean and variance information (Eq. 4 to 6), we compute the unconditional $\alpha-$quantile of the stock return as

$$q^{y_t}_{\alpha,t} = \mu_t + F_{-1}(\alpha)\sigma_{\ t} \tag{16}$$

Moreover, since Sklar's theorem allows us to express the joint distribution of y and x as $F_{X,Y}(x,y) = C(F_X(x), F_Y(y))$, we can compute the conditional quantiles using copula as

$$q^{y_t|x_t}_{\alpha,\beta,t} = F^{-1}_{y_t}\left(\hat{F}_{y_t}\left(q^{y_t|x_t}_{\alpha,\beta,t}\right)\right) \tag{17}$$

4 Data

We used the following stock indices: FTSE/JSE All Share (JSEOVER) for South Africa, Hermes Financial (EGHFINC) for Egypt, Nigeria All Share (NIGALSH), Nairobi SE (NSE20) for Kenya, FTSE 100 for United Kingdom and the S&P 500 COMPOSITE for the United Sates. These are tradeable indices readily available to market participants; hence, the returns are a true reflection of the gains an investor could make by holding them in a portfolio. The four African markets are the largest, in terms of listed companies, in their respective sub regions, that is Southern Africa, North Africa, East Africa, and West Africa. Another reason for this selection is that all the markets have daily data for a relatively long sample period. The data is of daily frequency, gleaned from Datastream and covers the period January 2000 to April 2014. The returns are calculated as 100 times the difference in the log of prices.

Table 2 shows the descriptive statistics. The mean percentage returns are close to zero in all cases and small compared to the standard deviations indicating high volatility in all the markets. Comparing the means, we notice Nigeria is the highest, followed by South Africa, whereas USA shows the lowest performance over the sample period. Furthermore, with the exception of Kenya, all the stock returns are negatively skewed and have excess kurtosis, suggesting a relatively higher probability of extreme negative returns compared to extreme positive returns. The Ljung-Box test confirms the presence of strong autocorrelation. The Jarque-Bera statistic (Jarque and Bera, 1980; 1981) strongly rejects the null hypothesis of normality in the return distributions. Finally, the ARCH-LM test (Engle, 1982) strongly confirms the presence of ARCH-effects in the individual series, thus, it suffices to model the return distributions with GARCH models.

Table 3 shows linear correlation among the six markets. Of importance is the correlation between the United States and African markets on one hand, and the correlation between the United Kingdom and African markets on the other hand. The ranking for the USA-related pairs from lowest to highest is USA-Nigeria, USA-Kenya, USA-Egypt and USA-South Africa. Similarly, the linear correlation from lowest to highest for the UK-related pairs is UK-Nigeria, UK-Kenya, UK-Egypt and UK-South Africa. With the exception of the USA-South Africa (0.5881) and UK-South Africa (0.3448), correlation is generally low among the remaining pairs. At the surface, the low correlation seems to be an indication of the possible benefits from diversification. It is instructive to note that the correlation coefficient only tell us about the average dependence over the entire distribution, thus, it would be misleading if one uses it to make inferences about diversification opportunities. Besides other shortcomings, correlation is a linear measure and is unable to capture the nonlinear dependence among the markets, hence the need for the copula technique, which is more robust.

5 Empirical Results

5.1 *Estimates of Marginal Models*

Prior to estimating the copula models, we apply an ARMA filtration to the stock return series to ensure the residuals have an expected return of zero and free from autocorrelation. We then test the fitted series for ARCH-effects using the ARCH-LM test and the results indicated that each of the series shows evidence of heteroscedasticity. We therefore determine the optimal lag length for each univariate GARCH and fit various specifications to the second moments. Table 4 shows the estimates of the ARMA-GARCH models for the stock returns. The best fitting models based on the Akaike information criterion (AIC) are AR(I)-GARCH(1,1) for South Africa, ARMA(1,1)-GJR-GARCH (1,1) for Egypt, ARMA(1,1)-GARCH(1,1) for Kenya, AR(2)-GARCH(1,1) for USA and AR(2)-GARCH(1,1) for Nigeria and U.K. Table 4 shows that the estimated conditional variance is impacted by past squared shocks (between 0.7334 to 0.2624) as well as past conditional variance (around 0.5886 to 0.9078).

Subsequent to the marginal specifications, we used the empirical distribution function to transform the standardized *iid* residuals into uniform margins, thus making our model semiparametric. Semiparametric models have much empirical appeal compared with the fully parametric models (Patton, 2012). We then carry out the goodness-of-fit for the marginal models by applying the Breusch-Godfrey serial correlation LM (BGLM) (Breusch, 1978; Godfrey, 1978) test to the PITs of the underlying error terms from each of the ARMA(p,q)-GARCH(p,q) processes. We carried out the BGLM test for the first four moments of the probability integral transforms (u and v) of the standardized residuals from the marginal models; that is, we regress $(u-\bar{u})^k$ and $(v-\bar{v})^k$ on 10 lags of both variables lags for. The p-values shown in Table 5 gives no indication of serial correlation, thus justifying the appropriateness of the marginal models.

5.2 *Copula Estimates*

Table 6 reports estimates of static and time-varying copula dependence between the US and African stock markets. The results for the UK-related pairs are shown in Table 7. Since the parameter estimates for the Gaussian and student-t copula captures the dependence between the markets, we can state that the higher the value of $\hat{\rho}$, the higher the dependence between the stock markets.

The $\hat{\rho}$ estimates in Table 6 are statistically significant for all African markets, with the exception of Kenya. The $\hat{\rho}$ estimates for South Africa shows a moderate positive relationship with the US and it is clearly distinguishable from Egypt and Nigeria, which show a weak positive linear relationship with the US stock market. Moreover, the time-varying Gaussian and student-t copula parameters both show the existence of time-varying dependence between the markets.

For the UK stock market, the Gaussian and student-t copula parameter estimates in Table 7 show the existence of weak uphill linear relationship with South Africa and Egypt only; $\hat{\rho}$ is not statistically significant for Kenya and Nigeria. Both the time-varying Gaussian and student-t copula parameters corroborate the existence of dynamic dependence for South Africa and Egypt.

Figure 1 depicts the temporal evolution based on the Gaussian copula GAS specification between the US and African stock markets (grey lines) on one hand, as well as the UK and African stock markets (black lines), on the other hand. Clearly, there is no similarity in the temporal evolution of dependence for the bivariate relationships. An upward trend can be found for the US-Nigeria pair, while Egypt shows significant peaks, coinciding with the sub-prime and Euro debt crises. The dynamic path for the Kenyan and UK-Nigeria pair is akin to a white noise process, while the US-South African pair exhibits mild clustering. These points to the fact that African markets do not respond uniformly to events in the advanced markets.

5.3 *Tail dependence between advanced and African stock returns*

The Gumbel (rotated Gumbel) captures upper (lower) tail dependence structure between the markets. Given that the implied tail dependence is defined as$2 - 2^{1/\kappa}$, we can say that a higher value of $\hat{\kappa}$ from the Gumbel (rotated Gumbel) indicates higher upper (lower) tail dependence between the stock markets. The static Gumbel (rotated Gumbel) parameter $\hat{\kappa}$ in Table 6 and 7 is statistically significant for both the US and UK related pairs. Comparing the values reveals moderate dependence for US-South Africa and weak dependence for all other pairs, except UK-Nigeria whose Gumbel copula parameter ($\hat{\kappa} = 1.000$) implies no upper tail dependence. Thus, we can say that African markets are generally less sensitive to the advanced markets.

Figure 2 illustrates the dynamic upper (lower) tail dependence based on the TVP Gumbel (rotated Gumbel) copula GAS specification. Dependence in the tails closely evolve and lower tail seems to be mostly greater than upper tail, suggesting the presence of asymmetry in some bivariate relationships. South Africa shows a more volatile tail dependence with the US compared to other African countries. Kenya's tail dependence with UK and US seems to be the least volatile among all the pairs. Although there is no clear similarity in temporal evolution of tail dependence for the bivariate pairs, most of them seemed to have responded to the Global Financial Crises and Euro Crisis with peaks of turbulence (e.g. US-Egypt, UK-Egypt, UK-South Africa, and US-Nigeria), which is in line with studies that point to an increase in financial market dependence during crisis (Kenourgios, Samitas & Paltalidis, 2011; Righi & Ceretta, 2013; Mensah & Premaratne, 2014). Yet, with the exception of South Africa, there is weak tail dependence for the African markets, suggesting a low probability of contagion or shock spillovers. The lack of strong association at the tails points to the mild segmentation of African markets from the advanced stock markets and this could be due to barriers such as the quality of information on African markets.

5.4 *Conditional Quantile Spillover Effects*

The weak dependence, particularly at the lower tails, is an indication that African markets are reasonably immune to risk spillovers from the advanced markets. In other words, the degree of comovement is too low to warrant the easy spread of contagious shocks along with its broad systemic implications. To shed more light on the spillover implications of the weak tail dependence uncovered in the previous paragraphs, we examine the impact of US and UK quantile stock return movements on African stock return quantiles We use information from the marginal and copula models to compute the unconditional and conditional stock return quantiles following Equation (12 -13) In the interest of space, we consider only extreme downwards (0.05) stock price movements.

Figure 3 depicts the dynamics of both unconditional and conditional stock return quantiles over the entire sample period. As can be visually perceptible by plots in Figure 3, we found that unconditional stock return quantiles were below the conditional quantiles for all African countries, suggesting the absence of any significant spill-over effects from the US and UK markets. This corroborates the weak lower tail dependence reported for the copula models. We can therefore say that extreme downward stock price movements in the US and UK do not have significant spillover effects on Africa's emerging stock markets.

6 Conclusion

This paper examines the dependence structure among African and advanced equity markets using daily stock prices from January 2000 to April 2014 and copulas. The empirical results show that dependence structure between African and international stocks varies overtime, but generally weak. Further, we find evidence of asymmetric and weak tail dependence for all the countries. Further, we find that that extreme downward stock price movements in the US and UK do not have significant spillover effects on Africa's emerging stock markets.

In general, the evidence presented has important implications for market participants and policy makers in diverse ways. First, the presence of weak dependence between African and advanced stock markets points to the potential gains for international investors holding African stocks. Our finding should regenerate interest amongst practitioners to reassess how assets are allocated for effective diversification. Second, our results imply that African markets are immune to risk spillovers from the more advanced markets and the tendency to boom or crash together is minimal. In light of recent volatility in global stock markets with the associated spread of contagious shocks from advanced to emerging markets, as well as the broad macroeconomic implications, our findings might be useful to policy makers and regulators, particularly in African countries, in designing and implementing appropriate intervention policies.

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Table 1: Copula Specifications

Copula	Distribution	Parameter Space	Independence	Lower tail dep	Upper tail dep
Normal	$C_N(u,v;\rho)=\Phi_\rho(\Phi^{-1}(u),\Phi^{-1}(v))$	$\rho\in(-1,1)$	$\rho=0$	0	0
Student-*t*	$C_T(u,v;\rho,d)=T_{d,\rho}(t_d^{-1}(u),t_d^{-1}(v))$	$\rho\in(-1,1)$ $d\in(2,\infty)$	$\rho=0$	$\vartheta T(\rho,d)$	$\vartheta T(\rho,d)$
Gumbel	$C_G(u,v;\kappa)=\exp\{-[(-\ln(u))^\kappa+(-\ln(v))^\kappa]^{1/\kappa}\}$	$\kappa\in(1,\infty)$	$\kappa=1$	0	$2-2^{1/\kappa}$
Rotated Gumbel	$C_{RC}(u,v;\kappa)=u+v-1+C_G(1-u,1-v;\kappa)$	$\kappa\in(1,\infty)$	$\kappa=1$	$2-2^{1/\kappa}$	0

Note: The column titled "Independence" shows the parameter values that lead to independence copula. u and v denotes the cumulative density functions of the standardized residuals from the marginal models and $0\le u,v\le 1$. Φ_ρ is the bivariate cumulative distribution of the standard normal with correlation coefficient ρ and $\Phi^{-1}$is the inverse function of the univariate normal distribution. $T_{d,\rho}$ is the bivariate student's *t* distribution with correlation coefficient ρ and degree of d, which captures the extent of symmetric extreme dependence; t^{-1} is the inverse function of the univariate Student's *t* distribution. κ denotes the parameters for the Gumbel and rotated Gumbel copulas.

Table 2: Descriptive statistics

	Mean	Std. Dev.	Skewness	Kurtosis	JB	$Q(2)$	$Q^2(2)$	ARCH(2)
South Africa	0.00045	0.0124	-0.1893	6.79	2244.98[a]	7.9277[b]	392.6[a]	180.43[a]
Egypt	0.00046	0.0162	-0.5519	12.54	14275.55[a]	62.003[a]	296.78[a]	144.19[a]
Kenya	0.00020	0.0094	0.3041	34.45	153138.70[a]	387.33[a]	1252.3[a]	644.41[a]
Nigeria	0.00053	0.0133	-0.8079	399.68	24357436.00[a]	47.995[a]	932.58[a]	917.64[a]
United States	-3.48E-06	0.0124	-0.1474	9.36	6275.25[a]	17.114[a]	529.25[a]	243.76[a]
United Kingdom	5.99E-05	0.0128	-0.1752	11.2060	10442.3200[a]	35.163[a]	661.16[a]	337.14[a]

Notes: The table displays the summary statistics for daily stock of the stock returns of the various markets from January 2000 to April 2012. Std. Dev. is the standard deviation. JB refers to the Jarque-Bera test for normality. $Q(2)$ and $Q^2(2)$ are the Ljung-Box-Q-statistics and Ljung-Box-Q2-statistics for serial correlation of order 2 in returns and squared returns. ARCH(2) is the Lagrange multiplier test for autoregressive conditional heteroscedasticity of order 2. [a] and [b] denote statistical significance at 1% and 5% , respectively.

Table 3: Linear Correlation

	US	UK	South Africa	Kenya	Nigeria
UK	0.5323				
South Africa	0.5881	0.3448			
Kenya	0.0303	0.0100	0.0227		
Nigeria	0.0046	0.0020	0.0201	0.0054	
Egypt	0.1292	0.0704	0.1497	0.0518	0.0254

Table 4: Estimates of the marginal models

	South Africa	Egypt	Kenya	Nigeria	USA	UK
Panel A: Conditional mean						
c	0.0008 [a]	0.0007 [a]	0.0005 [b]	0.0004 [b]	0.0004 [a]	0.0005 [a]
	(0.0002)	(0.0003)	(4.2573)	(0.0002)	(0.0000)	(0.0001)
φ_1	0.0393 [b]	-0.1940 [b]	0.0864 [b]	0.3451 [a]	0.8906 [a]	-0.0588 [a]
	(0.0176)	(0.0884)	(4.9666)	(0.0191)	(0.0320)	(0.0189)
φ_2				0.0529 [a]	0.0339 [c]	-0.0335 [b]
				(0.0175)	(0.0189)	(0.0170)
θ_1		0.3686 [a]			-0.9513 [a]	
		(0.0831)			(0.0250)	
Panel B: Conditional variance						
ω	0.0000 [a]	0.0000 [a]	0.0000 [a]	0.0000 [a]	0.0000 [a]	0.0000 [a]
	(0.0000)	(0.000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1	0.0867 [a]	0.0484 [a]	0.1256 [a]	0.2625 [a]	0.1004 [a]	0.0816 [a]
	(0.0098)	(5.0866)	(0.0038)	(0.0222)	(0.0076)	(0.0064)
β_1	0.8994 [a]	0.8398 [a]	0.8605 [a]	0.5886 [a]	0.8908 [a]	0.9078 [a]
	(0.0111)	(0.0044)	(0.0021)	(0.0238)	(0.0079)	(0.0069)
Asym		0.0818 [a]				
		(0.0105)				
$\alpha_1 + \beta_1$	0.9864	0.9132	0.9861	0.8510	0.9913	0.9895
Log Like	11564.61	10416.47	13074.77	12745.34	11842.44	11771.45

Notes: Daily returns for the Asian banking sector indices over the period between January 2000 and December 2012. Panel A contains the parameter estimates for the conditional mean, modelled using an ARMA(p,q) model; Panel B contains parameter estimates from GARCH(p,q) models of the conditional variance. c, φ_1, φ_2, θ_1 are the constant, AR(1), AR(2) and MA(1) in Eq(4). ω, α_1, β_1 are the constant, ARCH, and GARCH terms in Eq(6). Asym denotes the asymmetry term from the GJR-GARCH model. Values in parenthesis are the standard. [a] and [b] indicates statistical significance at 1% and 5%, respectively

Table 5: Goodness of fit tests

Breusch-Godfrey serial correlation LM test p-value				
	First moment	Second moment	Third moment	Fourth moment
South Africa	0.5808	0.9852	0.9969	0.9995
Egypt	0.4158	0.4172	0.9961	0.999
Kenya	0.7343	0.9474	0.6931	0.9899
Nigeria	0.3840	0.1053	0.2508	0.1611
USA	0.2497	0.1756	0.1560	0.1955
UK	0.5522	0.9945	0.9990	0.9907

Notes: The p-values for the test for serial correlations in the standardized residuals of the stock market indices, based on Breusch-Godfrey serial correlation LM at 10 lags. The test was carried out for four moments

Table 6: Estimates of static and time-varying copulas: US-related Pairs

Panel A: Parameter estimates for time-invariant copulas				
	South Africa	Egypt	Kenya	Nigeria
Gaussian copula				
$\hat{\rho}$	0.5692 [a]	0.1260 [a]	0.0084	0.0459 [a]
	(0.0108)	(0.0163)	(0.0178)	(0.0169)
AIC	1455.641	61.3942	2.2598	9.8206
Student-t copula				
$\hat{\rho}$	0.5740 [a]	0.1265 [a]	0.0076	0.0460 [a]
	(0.0097)	(0.0162)	(0.0179)	(0.0171)
$\hat{d}^{-1}$	0.1015 [a]	0.0287 [a]	0.0100	0.0100
	(0.0165)	(0.0137)	(0.0098)	(0.0100)
AIC	1501.1034	66.1012	4.7556	12.2578
Gumbel copula				
$\hat{\kappa}$	1.5571 [a]	1.0700 [a]	1.0086 [a]	1.0207 [a]
95%CI	[1.5203 1.5939]	[1.0478 1.0921]	[0.9950 1.0222]	[1.0021 1.0392]
AIC	1308.717	44.357	-85.1466	-43.082
Rotated Gumbel copula				
$\hat{\kappa}$	1.5860 [a]	1.0726 [a]	1.0096 [a]	1.0237 [a]
95%CI	[1.5472 1.6248]	[1.0502 1.0949]	[0.9944 1.0248]	[1.0050 1.0423]
AIC	1435.2998	48.302	-96.283	-38.247
Panel B: Parameter estimates for time-varying copulas				
	South Africa	Egypt	Kenya	Nigeria
TVP-Gaussian				
ψ_0	1.2956 [a]	0.2199 [a]	0.0063	-0.0500
	(0.0909)	(0.0992)	(0.0423)	(0.4353)
ψ_1	0.0336 [a]	0.0073	0.0293 [a]	0.0017 [a]
	(0.0077)	(0.0044)	(0.0081)	(0.0008)
ψ_2	0.9848 [a]	0.9962 [a]	0.9000 [a]	0.9979 [a]
	(0.0075)	(0.0052)	(0.0436)	(0.0009)
AIC	-1588.8831	-81.5262	-11.7411	-8.3358
TVP-Student-t				
θ	15.0156 [a]	42.2699	168.7239 [a]	109.3105 [a]
	(3.8400)	(84.475)	(3.9330)	(21.8590)
$\tilde{\alpha}$	0.0285 [a]	0.0082)	0.0280 [a]	0.0017
	(0.0090)	(0.0090)	(0.0080)	(0.0010)
$\tilde{\beta}$	0.9618 [a]	0.9882 [a]	0.8746 [a]	0.9979 [a]
	(0.0140)	(0.0170)	(0.0360)	(0.0011)
AIC	-1615.879	-85.6932	-10.9631	-7.5584
TVP-Gumbel				

ϖ	-0.0090 [a]	-0.0080 [a]	-0.1873	-0.0128
	(0.0019)	(0.0024)	(0.3425)	(0.0174)
$\overline{\alpha}$	0.0754 [a]	0.0736 [a]	-0.0066	0.0356 [a]
	(0.0178)	(0.0223)	(0.0898)	(0.0171)
$\overline{\beta}$	0.9849 [a]	0.9972 [a]	0.9581 [a]	0.9965 [a]
	(0.0041)	(0.0009)	(0.0816)	(0.0048)
AIC	-1401.9678	-67.4109	6.6844	-0.1744
TVP-rotated Gumbel				
ϖ	-0.0082	-0.0084	-0.0144	-0.0147
	(0.0149)	(0.0103)	(0.0357)	(0.0138)
$\overline{\alpha}$	0.0756	0.0588	0.0321	0.0355 [a]
	(0.0730)	(0.0380)	(0.0463)	(0.0138)
$\overline{\beta}$	0.9852 [a]	0.9968 [a]	0.9963 [a]	0.9958 [a]
	(0.0269)	(0.0041)	(0.0094)	(0.0040)
AIC	-1530.5475	-72.8748	15.2325	-3.6294

Notes: the table reports the maximum likelihood estimates for the different pair-copulas. 95% confidence intervals are given in brackets. Standard errors are given in parenthesis. [a] indicates significance at 1%.

Table 7: Estimates of static and time-varying copulas: UK-related Pairs

Panel A: Parameter estimates for time-invariant copulas				
	UK- South Africa	UK-Egypt	UK-Kenya	UK-Nigeria
Gaussian copula				
$\hat{\rho}$	0.3478 [a]	0.0613 [a]	-0.0039	0.0130
	(0.0161)	(0.0178)	(0.0162)	(0.0140)
AIC	480.7052	15.9648	2.0566	2.626
Student-t copula				
$\hat{\rho}$	0.3498 [a]	0.0624 [a]	-0.0042	0.0136
	(0.0148)	(0.0182)	(0.0162)	(0.0142)
$\hat{d}^{-1}$	0.0798 [a]	0.0100	0.0100	0.0100 [a]
	(0.0227)	(0.0184)	(0.0143)	(0.0030)
AIC	505.5392	20.1938	5.0554	3.9482
Gumbel copula				
$\hat{\kappa}$	1.2555 [a]	1.0229 [a]	1.0030 [a]	1.0000 [a]
95%*CI*	[1.2268 1.2841]	[1.0030 1.0427]	[0.9867 1.0193]	[0.9832 1.0169]
AIC	428.5182	-36.7376	-85.1466	-87.8474
Rotated Gumbel copula				
$\hat{\kappa}$	1.2655 [a]	1.0405 [a]	1.0010 [a]	1.0052 [a]
95%*CI*	[1.2359 1.2952]	[1.0202 1.0609]	[0.9876 1.0145]	[0.9875 1.0229]
AIC	462.2446	-6.4062	-96.283	-75.4704

Panel B: Parameter estimates for time-varying copulas				
	South Africa	Egypt	Kenya	Nigeria
TVP-Gaussian copula				
ψ_0	0.6445 [a]	0.1207 [a]	-0.0106	0.0266
	(0.1567)	(0.0571)	(0.0355)	(0.0345)
ψ_1	0.0069 [a]	0.0028	0.0100	0.0093
	(0.0020)	(0.0017)	(0.0073)	(0.0096)
ψ_2	0.9985 [a]	0.9965 [a]	0.8642 [a]	0.8121 [a]
	(0.0015)	(0.0037)	(0.1121)	(0.1803)
AIC	-522.6071	-12.4225	4.1819	4.5830
TVP-Student-t				
θ	14.6947 [a]	26.7856 [a]	53.5511	198.7639 [a]
	(3.9230)	(11.0560)	(84.383)	(2.2860)
$\tilde{\alpha}$	0.0063 [a]	0.003 [b]	0.0108	0.0098
	(0.0020)	(0.0020)	(0.0090)	(0.0110)
$\tilde{\beta}$	0.9923 [a]	0.9937 [a]	0.8558 [a]	0.8015 [a]
	(0.0030)	(0.0030)	(0.0600)	(0.0960)
AIC	-539.9817	-17.1798	2.8237	4.862
TVP-Gumbel				

ϖ	-0.0030 [c]	-0.0125	-0.0149 [a]	-0.1601
	(0.0015)	(0.0077)	(0.0000)	(0.2287)
$\overline{\alpha}$	0.0281 [a]	0.0390 [a]	0.0295	0.0400
	(0.0070)	0.0192)	(0.0759)	(0.5577)
$\overline{\beta}$	0.9979 [a]	0.9964 [a]	0.9962 [a]	0.9622 [a]
	(0.0011)	(0.0022)	(0.0010)	(0.0541)
AIC	-465.1842	-2.8861	11.7838	9.3908
TVP-Rotated Gumbel				
ϖ	-0.0026 [a]	-0.0121 [a]	-0.0183 [a]	-0.1783 [a]
	(0.0007)	(0.0027)	(0.0000)	(0.0000)
$\overline{\alpha}$	0.0237 [a]	0.0406 [c]	0.0148	0.0070
	(0.0068)	(0.0217)	(0.0151)	(0.0540)
$\overline{\beta}$	0.9981 [a]	0.9964 [a]	0.9956 [a]	0.9606 [a]
	(0.0004)	(0.0006)	(0.0007)	(0.0059)
AIC	-491.4105	-16.1150	14.6976	6.1919

Notes: the table reports the maximum likelihood estimates for the different pair-copulas. 95% confidence intervals are given in brackets. Asymptotic standard errors are in parenthesis. [a] and [b] indicates significance at 1% and 5%, respectively.

Figure 1: Time-varying Gaussian dependence of the USA, UK and African stock markets

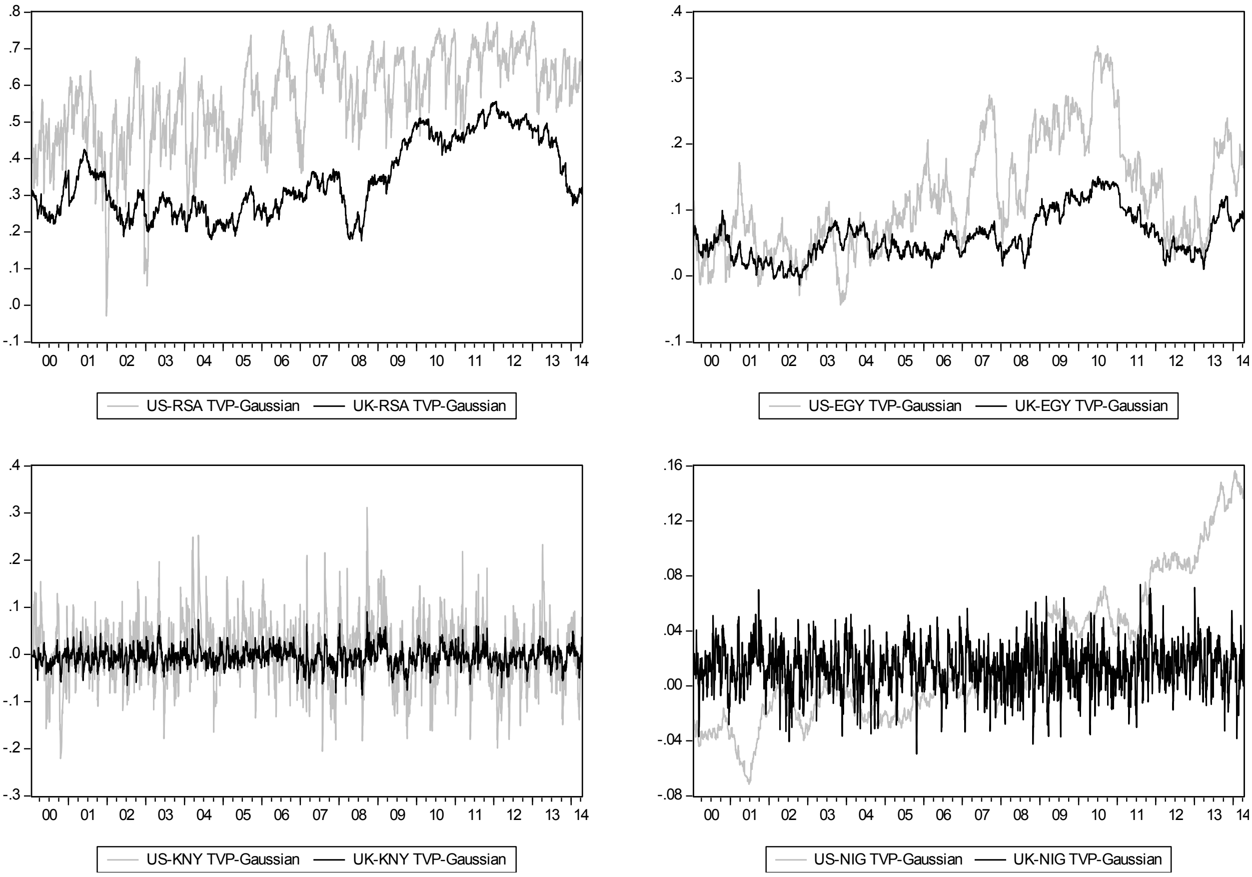

Figure 2: Time- varying dependence of the US and UK with African stock markets

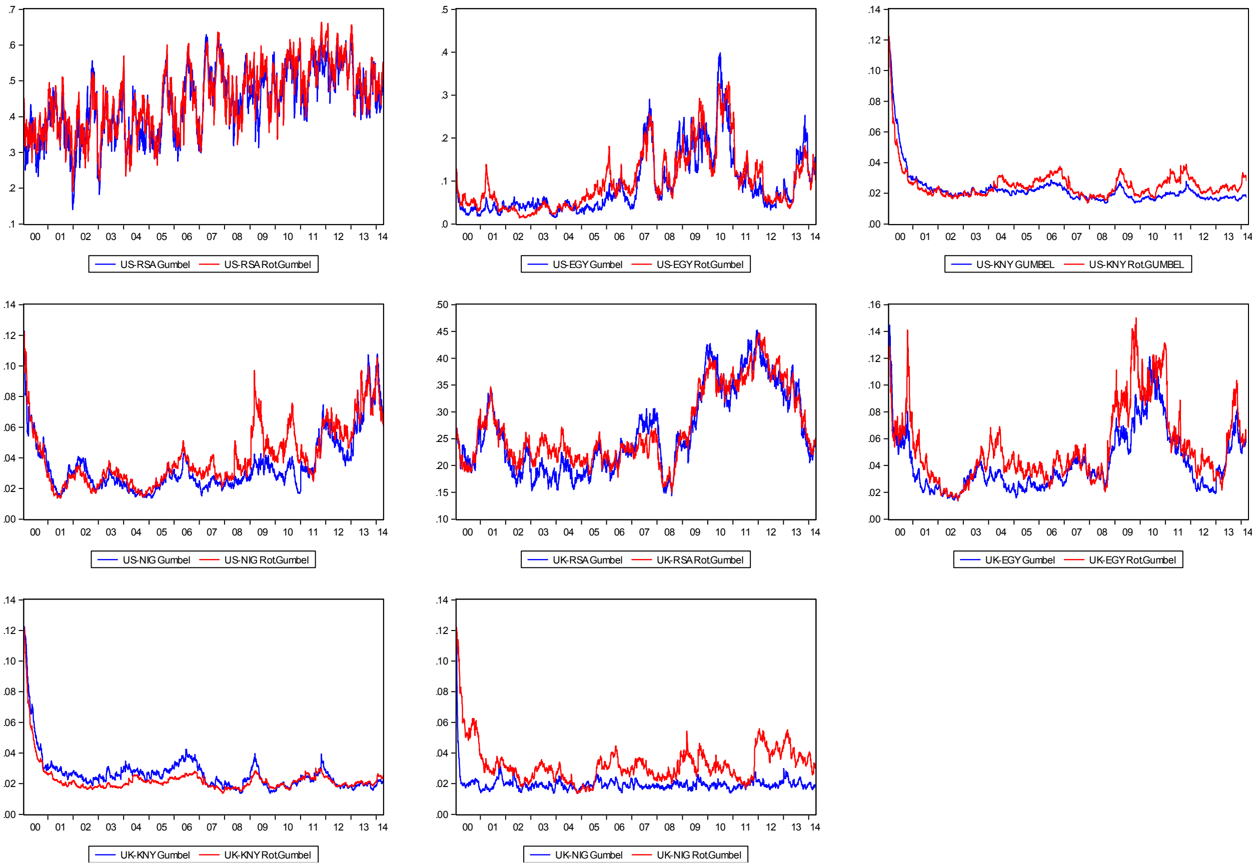

Figure 3: Downside Value-at-Risk (VaR) and conditional Value-at-Risk (CoVaR) for African stock market returns