A regime-switching skew-normal model of contagion in some selected stock markets

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Abstract
This study examined the contagion and structural break between Nigerian Stock Exchange Market (NSE) and some selected stock markets, namely: Ghana, South Africa (SA), Tunisia, and the United States. Two periods were considered: the crisis period (1st May 2016 to 31st December 2017) and the calm period (1st January 2018 to 31st December 2019). Following the work of (Chan, J., Fry-McKibbin, R. & Hsiao C. (2018). A Regime switching skew-normal model of contagion. Studies in Nonlinear Dynamics and Econometrics, Volume 23, Issue 1), the study used the Regime Switching Skew-Normal (RSSN) model which is capable of measuring contagion and structural breaks between markets. Our results indicated evidence of a structural break between the crisis and calm periods, which is a prerequisite for contagion. Furthermore, the study found a moderate contagion between Nigeria and SA stock markets but an absence of contagion between Nigeria and the remaining stock markets, suggesting capital flights from Nigeria to SA for safety during the 2016 economic recession. However, we were unable to find any evidence of capital reversal to Nigeria from SA during the calm period, implying an existence of an asymmetric relationship between Nigeria and South African stock markets. The absence of contagion between Nigeria and the selected African stock markets, suggests there is no significant economic cooperation and cross-border portfolio investment flow among the countries. This development further underpins the imperativeness of the full implementation of the African Continental Free Trade Agreement (AfCFTA), which encourages economic activities and investment flow on the continent.

Keywords AfCFTA · African Stock Markets · Regime Switching Models · Bayesian Model · Contagion

JEL Classification F15 · G15 · G17 · R11 · F36

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**Introduction**

Empirical stylized facts on financial contagion during crisis periods have produced evidence that suggests markets react differently during a crisis and calm periods. Assessing the co-movement of financial markets and vulnerability in different periods of market crisis have been empirically studied with established evidence well documented. Financial assets are exposed to different episodes of crisis and have responded differently in each of these crises. (See, among others, Smith 2007; Guidolin and Timmermann, 2008; Fry et al. 2010; Poti and Wang 2010; Lambert and Hubner 2013; and more recently, Chan et al. 2018).

A careful examination of the established empirical evidence on the African stock markets showed that financial contagion during crisis periods has not been well explored. Additionally, the empirical evidence from the African stock markets has yet to sufficiently deal with what motivates investors to switch to a crisis regime and/or issue of capital flight to safety and, therefore, a consistent finding on the risk preference of investors during the crisis period cannot be established. Put differently, volatility spillover mainly from developed stock markets to emerging markets of Africa dominate the empirical stylized facts of the African stock markets. (See, among others, Appiah-Kusi and Pescetto 1998; Korkmaz et al. 2012; Sugimoto et al. 2014; Syriopoulos et al. 2015; Yavas and Rezayat 2016; Fowowe 2017; Baumöhl et al. 2018; and more recently, Hung 2020; Mensi et al. 2021; Atenga and Mougoué 2021). Although there is a plethora of studies that examined financial contagion in African stock markets during the episodes of crisis as in the reported Collins and Biekpe (2003), Khallouli and Sandretto (2012), Ahmad et al. (2013), Boako and Alagidede (2017), Abdennadher and Hellara (2018), Anyikwa and Le Roux (2020), and Aderajo and Olaniran (2021). These studies have serious flaws in the model design as a result of the nature of financial contagion during crisis periods.

The empirical motivation of the study is based on methodological flaws in estimating financial contagion during crisis periods in African stock markets. Recently, Chan et al. (2018) extended Hamilton’s (1993) regime-switching model to a multivariate framework that features joint skew-normal distribution. The incorporation of skew-normal distribution helps to capture any form of non-normality in the joint distribution of asset returns and, therefore, flexible enough to accommodate linear and non-linear comovement between asset returns that are likely to emerge during a switch to a crisis regime. There is substantial evidence of significant crisis in the African stock markets which suggests possible structural breaks in the data generating process. Assuming away this feature, as observed in many empirical works using African stock market, will produce bias estimates of the model parameters.

Various methods have been used by different authors to study the relationship between stock and bond markets. They include the breakpoint tests approach (Billio and Caporin 2005; Gravelle et al. 2006), the Smooth transition model with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (Dungey et al. 2015), and another form of regime-switching model (Billio and Caporin...
2005; Gravelle et al. 2006). Most of these works examine the contagion relationship between markets while assuming normality in the return series. Following the work of Chan et al. (2018) who studied the contagion between the US and European equity markets during the global financial crisis of 2007, the use of regime-switching models of contagion that assume Skew-normal emerged.

While a look at the literature database showed that research on the stock market contagion is indeed substantial, we also found that, despite this liberal presence of literature on the topic, we could not, to the best of our knowledge, identify any research within the African capital markets that utilized a regime-switching skew-normal model for analysis. Secondly, there has not been any other study that analyzed capital flight and financial contagion during the crisis in Africa. The objective of this paper, is, therefore, to test some empirical hypothesis on the contagion and structural breaks in the selected stock markets during the crisis and calm periods. Specifically, the study investigates a potential existence of flight to safety (contagion) by equity investors. Where contagion exists, the study investigates whether it is linear or non-linear. In other words, is the flight in or out between markets symmetric or asymmetric? And finally, the study investigates the risk preference of investors in African stock markets. This was achieved using the Markov Chain Regime Switching model that assumes skewed-normal in the distribution of assets return. The model was estimated using the Bayesian procedure. From the results, the following evidence emerged: (i) Existence of a structural break between the crisis and calm periods, which is a prerequisite for contagion; (ii) a moderate contagion between Nigeria and SA stock markets but an absence of contagion between Nigeria and the remaining stock markets, suggesting capital flights from Nigeria to SA for safety during the 2016 economic recession. However, we were unable to find any evidence of capital reversal to Nigeria from SA during the calm period, implying the existence of asymmetric relationship between Nigeria and the South African stock markets.

The rest of the paper is organized as follows: a review of relevant literature takes the Literature section; theoretical and empirical models are discussed in the Theoretical and Empirical methodology section, Empirical evidence section presents and analyzes the results, while the paper was concluded in the Conclusion and policy implications section.

**Literature review**

To better understand the amount and the depth of study that have been conducted in the equity market, especially, vis-à-vis market contagion, we look at literature across this capital market segment to identify empirical and theoretical gaps in the literature. Lyócsa and Horváth (2018) using quantile regression with daily data, came up with a new approach to evaluate stock market contagion and examine whether there exists any nexus between increased unanticipated volatility during extreme market downturns in the originating market and increased return co-exceedance in the recipient market. Authors found evidence of contagion from the U.S.A stock market to the six largest developed stock markets of Japan, the United Kingdom, France,
Germany, Hong Kong, and Canada. Authors also discovered a prevalence of contagion across events, i.e., crisis and calm.

Su (2021) conducted a heterogeneity study of large and small stock market structures using a causality test to determine the degree of cross-market contagion. The author found less inner-market contagion but more cross-market contagion in the large stock markets, while more inner-market contagion and less cross-market contagion were observed across smaller stock markets. Authors further found that contagion from small markets to larger ones is usually more adverse than those from large to small, except the United States stock market which appeared immune to small markets feedback. In the same vein, Wang et al. (2017) tested for stock market contagion during the Global Financial Crisis (GFC) from the United States to other G7 member countries and the BRICS countries using multiscale correlation contagion statistics. Authors discovered cross-market correlations between the United States and those countries are dependent on the time scale. For instance, the results indicated that contagion from the United States to China, Japan, and Brazil occurs when the time scale is longer than 50 days.

In their study, Markwat et al. (2009) used a novel unifying framework to model the occurrence of local, regional, and global crashes relative to historical occurrences of these differing crashes and financial variables. The authors concluded that global crashes do not happen suddenly but are usually preceded by local and regional crashes. The results further found that interest rates, bond returns, and volatility affect the probabilities of crash occurrence or the types. In their follow-up study, Markwat et al. (2009) on “Contagion as a Domino Effects in Global Stock Markets, in which authors similarly employed a novel framework based on ordered logit regressions to model the occurrence of local, regional, and global crashes as a function of their historical occurrences and financial variables. The results again confirmed the earlier finding that global crashes are typically preceded by local and regional crashes. Authors further affirmed crash probabilities due to the effects of interest rates, bond returns, and stock market volatility.

In their effort to examine any possible contagion effect between energy and stock markets during the Global Financial Crisis (GFC), Wen et al. (2012) applied time-varying copulas to analyze the WTI oil spot price, the S&P500 index, the Shanghai stock market composite index and the Shenzhen stock market component index returns. Authors found significant evidence of growing dependence between crude oil and stock markets after the collapse of Lehman Brothers, evidencing the existence of the type of contagion as defined by (Forbes and Rigobon 2002). In their study, Baur and Miyakawa (2014) analyzed the short-run and the long-run linkages between stock market performance and macroeconomic performance for a significant number of countries. The results showed that stock market returns do not predict future macroeconomic changes for most countries.

Trenca and Dezsi (2012) attempted to evaluate the behavior of the Romanian stock market vis-à-vis financial contagion from the global market using a 3-state Markov Switching Vector Autoregressive (MS-VAR) model to analyze data from 1997 to 2012. The study, however, found no real contagion effect in the Romanian market during the Global Financial Crisis but confirmed comovements due to markets integration. Given this outcome and the fact that real interaction between the
Romanian and the global market is time-varying, the authors concluded that investors in Romania are not able to benefit from international portfolio diversification.

Similarly, Zhou et al. (2018) investigated the contagion effect between stock markets in Asia, Europe, and the United States under time-varying frequencies, using the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) model. Authors found that shocks from “irregular events and extreme events” can both be transmitted between different stock markets. However, the results further indicated that, while shocks from irregular events can pose sudden and short-term risk contagion to stock returns, shocks from extreme events on the other hand can pose positive and sustained risk contagion to stock returns. Ahlgren and Antell (2010) in their study, used the co-breaking test to model comovements between stock markets in times of crisis and also test for contagion. Authors found evidence of co-breaking that was precipitated by the 2001 terrorism acts on the World Trade Center. While the results indicated evidence of markets linkage, no contagion effect was detected, an outcome that has implications for investors, risk managers, and regulatory authorities.

In their study, Okorie and Lin (2021) investigated the fractal contagion effect of the Covid-19 pandemic on the stock markets in 32 countries using the Detrended Moving Cross-Correlation Analysis (DMCA) and Detrended Cross-Correlation Analysis (DCCA) methods. Their results showed a fractal contagion effect of the COVID-19 pandemic on the stock markets. However, the results also showed that this fractal contagion effect disappears over time for both the stock markets’ return and volatility. Aderajo and Olaniran (2021) conducted an empirical evaluation of the dynamic correlation analysis of financial contagion with data from five African countries: South Africa, Nigeria, Egypt, Kenya, and Tunisia. The authors employed the Dynamic Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroskedasticity (DCCM-GARCH) model to examine the contagious effect of the US on the above-listed African markets. The results indicated a significant linkage between the returns of the US market and the African market’s performance. The results further showed that contagion did exist in the crisis period, while a continued correlation or herding existed in the post-crisis period.

Wang and Lai (2013) examined the contagion effects between stock markets in Vietnam, China, Japan, Singapore, and the U.S.A. For the analysis, the authors constructed a bivariate EGARCH model of dynamic conditional correlation coefficients. The results validated a presence of contagion effects between the Vietnamese stock market and four other stock markets, with Japan, China, Singapore, China, and the U.S.A. The results also showed a stronger contagion effect from the Japanese stock market to the Vietnamese market in comparison to the stock markets of China, Singapore, and the U.S.A. In another study, Fang and Egan (2018) studied the possible contagion effects of oil prices on the Chinese Stock market. Authors computed time-varying cut-offs using the Generalized Pareto Distribution (GPD) function to estimate excess returns. Further, the authors examined the probability of Chinese stock market exceedances associated with oil price exceedances, using the Multinomial Logit Model (MNL). The results showed a relatively weak although not negligible contagion effect between the oil price and the Chinese stock market returns. Invariably, the authors reiterated that during the
crisis period, the presence of contagion renders any portfolio investment diversification efforts between oil and the Chinese stock market redundant.

In a similar study, Ding et al. (2017) used the Principal component analysis method to build a Chinese stock market investor sentiment index and then applied the Structural Vector Autoregressive (SVAR) model to analyze the contagion effect of international crude oil price fluctuations on country’s stock market investor sentiment. According to the results, international crude price fluctuations significantly granger cause Chinese stock market investor sentiment. For perspective, the authors found that a 1% fluctuation in the international crude oil price would cause the stock market sentiment to negatively fluctuate at about 3.94%. In the short-run efficacy, a 1% fluctuation in the international crude oil price would lead to the stock market investor sentiment during the period to negatively fluctuate by 1.02%.

Pan et al. (2015) extended Hong et al.’s (2007) model-free test to examine the contagion from the crude oil market to stock markets. The authors conducted a simulation experiment that revealed strong evidence of contagion between crude oil and stock markets. Similarly, Chiang et al. (2007) used a dynamic conditional-correlation model on nine Asian daily stock-return data series from 1990 to 2003. The authors found evidence of the contagion effect from the crude oil market to the stock markets. The authors identified two phases of the Asian crisis using correlation-coefficient analysis. The first phase indicated an increase in correlation (contagion); while the second phase showed a continued high correlation – heading.

While a look at the literature database showed that research on the stock market contagion is indeed substantial, we also found that, despite this liberal presence of literature on the topic, we could not, to the best of our knowledge, identify any research within the African capital markets that utilized a regime-switching skew-normal model for analysis. Second, there has not been any other study that analyzed capital flight and financial contagion during crisis.

**Theoretical and empirical methodology**

**Strategy of the work**

This study intends to provide uni-directional evidence, as to whether there was equities flight to other jurisdictions for safety purposes during a crisis in Nigeria, and if there was, who were the beneficiaries? To do that, we defined a crisis period (1st May 2016 to 31st December 2017), a period when Nigeria experienced economic recession, to measure the extent of the flight, and a calm period ((1st January 2018 to 31st December 2019). In addition, the comparison between the crisis and calm periods will enable the study to establish the presence of structural breaks in returns which is a prerequisite for equities to change jurisdiction.
Data and definition of variables

To accommodate the recession experienced in Nigeria during 2016/2017, this study used daily equity prices from 1st May 2016 to 31st December 2019. The period is divided into crisis (1st May 2016 to 31st December 2017) and calm period (1st January 2018 to 31st December 2019). The data were collected from Bloomberg and were used to analyze the relationship between pairs of major stock markets in Africa. The selected markets are the Nigerian Stock Exchange Market (NSE), the Ghana Stock Exchange, the New York Stock Exchange (NYSE), The Johannesburg Stock Exchange (South Africa), and the Tunisian Exchange. The rationale for the choice of these selected stock markets is based on the size as they represent 70 percent of the total equity traded in Africa while the US stock market serves as a reference for studies that analyze volatility spillover, financial

![Equity returns for some selected stock markets](image-url)

Fig. 1 Equity returns for some selected stock markets
contagion and comovement of assets. For visualization of the return series, see Fig. 1.

**Regime switching skew-normal model (RSSN)**

The Regime Switching Skew Normal (RSSN) framework emanated from the combination of the regime-switching model by Hamilton (1993) and Sahu et al. (2003) who proposed the skew-normal distribution. The underlying assumption is a joint multivariate skewed-normal distribution such that the elements on the diagonal of the matrix represent skewness and co-skewness by off-diagonal elements. The assumption of skewed-normal distribution enables us to capture the asymmetries, heavy tails, heteroscedasticity, and time-varying linear and non-linear co-moments among assets. To understand the model, following the work of Sahu et al. (2003), let us assume the representation of the following latent variables.

\[
y_t = \mu + \eta W_t + u_t
\]

(1)

\[
u_t \overset{iid}{\longrightarrow} N(\alpha, \Sigma)
\]

(2)

\[W_t \overset{iid}{\longrightarrow} N\left(1_m, I_m\right) I(W_{jt} > c, j = 1, \ldots, m)
\]

where \(y_t = [y_{it}, \ldots, y_{nt}]^\prime\) is n-dimensional random vector, \(\mu\) is nx1 vector of constant, \(\eta\) is mxm skewness and co-skewness matrix. The \(W_t = [z_{it}, \ldots, z_{nt}]^\prime\) is an n-dimensional random vector, the \(\Sigma\) is mxm variance–covariance matrix. The \(1\) is an mx1 column of ones, \(I_m\) is an identity matrix while \(I(\cdot)\) is an indicator function that takes the following:

\[
I(\cdot) = \begin{cases} 
1 & \text{if } W_{jt} > C \\
0 & \text{if } W_{jt} \leq 0 
\end{cases}
\]

There are two key assumptions regarding the nature of. Firstly, Sahu et al. (2003) assume that \(W_t\) to be a diagonal matrix hence it only measures skewness. The other assumption is that \(W_t\) can be a lower or upper triangular matrix with elements of the diagonal measuring co-skewness between elements. The density function of \(y_t\) concerning \(W_t\) is given as:

\[
F_{SN}(y_t; \mu, \Sigma, N) = \frac{2^m}{\det(\Sigma + \eta^2)^{0.5}} f_N(\Sigma + \eta^2)^{-0.5} (y_t - \mu) pr(V > c)
\]

(3)

where \(V\) is given as If the \(\eta=0\), then the skew-normal distribution as described in 3.1 to 3.3 become multivariate normal distribution with function given as:
Now, introducing regime-switching into skew-normal distribution such that each element has a multivariate skew-normal distribution, but the parameters are allowed to differ across the state \((s)\). Now assuming state dependency in 3.1 to 3.3, we have:

\[
F_{SN}(y_t; \mu, \Sigma) = \frac{1}{\text{det}(\Sigma)^{0.5}} f_N(\Sigma^{-0.5}(y_t - \mu))
\]

Now, introducing regime-switching into skew-normal distribution such that each element has a multivariate skew-normal distribution, but the parameters are allowed to differ across the state \((s)\). Now assuming state dependency in 3.1 to 3.3, we have:

\[
y_t = \mu_{st} + \eta_{st} W_t + u_t
\]

\[
u_t \overset{iid}{\sim} N(o, \Sigma_{st})
\]

\[
W_t \overset{iid}{\sim} N(1_m, I_m) I(W_{jt} > c, j = 1 \ldots \ldots \ldots m)
\]

The switching parameters are and \([\mu_1, \eta_1, \Sigma_1]\) if we assume the parameters to switch across two regimes. However, this can be extended to multiple regimes following the same principle as described in the regime-switching literature. Assuming the two regimes dependent parameter given that. The process describing \(s_t\) follows the standard Markov transition given as:

\[
pr(s_t = 1/s_{t-1} = i) = p_{i,t} \text{ for } i. \text{ However, this can be extended to other forms of regime-switching models such as threshold and smooth models. To measure the relationship between two markets, the correlation coefficient } p_{ij} \text{ can be calculated as:}
\]

\[
p_{ij} = \frac{\Sigma_{ij, st}}{\sqrt{\Sigma_{ii, st}} \sqrt{\Sigma_{jj, st}}}
\]

The contagion relation between two markets happens if there is an increase in the magnitude of the correlation coefficient from a period of stability called great moderation in Chan et al. (2018) to a crisis period. In another word, if there is a contagion relationship between markets, the flight to safety during the crisis period as measured by the correlation coefficient is expected to increase. However, in the case of structural breaks, it is expected that the mean for the assets in one market during the crisis period compared to the stability period reduces; this is because returns are expected to reduce during the crisis period. For a detailed explanation of this, see Table 1.

**Bayesian analysis**

This study uses the Bayesian method for the analysis. This involves drawing the joint posterior distribution from the likelihood, which represents the data, and the priors that entered the model in form of a probability distribution. The parameters have joint likelihood but with priors. To understand the likelihood function, consider the following specification:
\[
\begin{align*}
\text{Joint contagion} & \quad (i \neq j) \\
\text{Correlation} & \quad P \\
\text{Co-skewness} & \quad \text{BF} \\
\text{Cov. & co-skewness} & \quad \text{BF} \\
\text{Structural break test} & \quad P \\
\text{Variance} & \quad \text{BF} \\
\text{Skewness} & \quad \text{BF} \\
\end{align*}
\]

where the priors for the two model parameters are given as:

\[
\beta_{st} \sim N\left(\beta, V\right) \text{ and } \Sigma_{st} \sim IW\left(T, S\right)
\]

To get the posterior distribution, as Bayes rule suggests, we take the product of the prior with the likelihood and the resultant is the joint posterior distribution:

\[
\pi(\theta, W, s/y) \propto f(y/W, \theta, s)
\]

Assuming prior independence between \(\beta\) and \(\Sigma\), the joint posterior density is given by:

\[
\pi(\theta) = \pi(\beta_{0})\pi(\beta_{1})\pi(\Sigma_{0})\pi(\Sigma_{1})
\]

The posterior distribution for \(\beta_{s}, s=0,1\), condition on \(y, W, \Sigma_{0}, \Sigma_{1}\) and \(s\) is given as:

\[
\left(\beta_{s}/y, W, \Sigma, s\right) \sim N_{q}\left(\hat{\beta}_{s}, D_{\beta_{s}}\right), i = 0, 1
\]

where:

\[
D_{\beta_{s}} = \left[V_{-\beta}^{-1} + \sum_{t=1}^{T} 1(s_t = i)X'_{st}X_t\right]^{-1} \quad \beta_{s} = D_{\beta_{s}} \left[V_{-\beta}^{-1}\beta - \sum_{t=1}^{T} 1(s_t = i)X'_{st}\Sigma_{st}^{-1}y_t\right]
\]

Furthermore, the posterior distribution for \(\Sigma, i = 0, 1\) conditioned on \(y, W, \beta_{0}, \beta_{1}\) & \(s\) with inverse Wishart distribution is:

\[
f(y/W, \theta, s) = (2\pi)^{-MT/2} \prod_{t=1}^{T} |\Sigma_{st}|^{0.5} \exp \left[ -\frac{1}{2} \sum_{t=1}^{T} [y_t - X_t\beta_{st}]' \Sigma_{st}^{-1} [y_t - X_t\beta_{st}] \right]
\]
\[ \sum_s y, W_s, \beta, s \sim IW (\sigma \Sigma_t, \beta \Sigma_t) \]

where \( \sigma \Sigma_t = \sigma \Sigma + \sum_{i=1}^T 1(s_t = t) \) & \( S \Sigma_t = S - \sum_{i=1}^T 1(s_t = 1) (y_t - X_t \beta_s) (y_t - X_t \beta_s) \)

For the latent variable, \( W_s \) are drawn independently conditional on \( y, \beta_0, \beta_1, \Sigma_0, \Sigma_1, s \). In terms of a probability distribution, each \( W \) is assumed to follow independent truncated multivariate normal distribution given as:

\[ (W_t/y, \theta, s) \sim IND N \left( W_D_{st} \right) I(W_{jt} > c, j = 1, ..., m) \]

where \( D_{st} = (I_m + S_{st}^{-1} \delta_{st})^{-1} \)

\[ W = D_{st} (c I_m + \delta_{st} S_{st}^{-1} (y_t - \mu_{st})) \]

**Empirical evidence**

This section presents the empirical evidence of the study. The estimates of models 1–3 were generated using the Gibbs sampler, from 200,000 iterations with the first 20,000 burns-in to achieve convergence. In terms of the assumptions of the initials of the priors, the study follows the work of Chan et al. (2018). The main thrust of this paper is to investigate the possibility of a contagion relationship between

|                | Nigeria | Ghana   | South Africa | Tunisia | USA     |
|----------------|---------|---------|--------------|---------|---------|
| Crisis Period  |         |         |              |         |         |
| Mean           | 31,337.37 | 3,520.55 | 48,940.07    | 5,433.928 | 11,698.46 |
| Minimum        | 22,456.32 | 1,777.040 | 42,422.36    | 4,968.70 | 8,146.52 |
| Maximum        | 43,039.42 | 22,014.29 | 55,188.34    | 6,376.08 | 14,455.28 |
| Std. Dev       | 5,470.564 | 1,670.945 | 2,932.427    | 327.83  | 1,294.59 |
| Skewness       | 0.54     | 1.65    | –0.005       | 1.15    | –0.17   |
| Correlation    | 0.00     | –0.30   | 0.39         | –0.16   | –0.53   |
| Co-skewness    | 0.00     | –112.88 | 362.82       | –11.24  | –226.46 |
| Calm Period    |         |         |              |         |         |
| Mean           | 33,156.16 | 4,564.98 | 49,942.78    | 7,208.41 | 16,027.23 |
| Minimum        | 26,092.82 | 1,012.70 | 44,417.70    | 6,203.27 | 14,421.49 |
| Maximum        | 44,912.53 | 4,775.80 | 54,575.94    | 8,422.13 | 17,827.75 |
| Std. Dev       | 5,496.85 | 242.52  | 2,099.89     | 453.14  | 846.73  |
| Skewness       | 0.61     | –11.79  | –0.57        | 0.72    | –0.05   |
| Correlation    | 0.00     | –0.11   | 0.54         | –0.05   | –0.98   |
| Co-skewness    | 0.00     | –2.25   | 328.75       | –4.41   | –342.95 |
Nigeria, Ghana, SA, and Tunisia being emerging economies within Africa and the US which is the major Nigerian trading partner.

Table 2 presents descriptive statistics of the data used in estimation and provides a preliminary investigation of the contagion among the selected stock markets. The skewness, co-skewness, and correlation between the indices are shown in Table 2, alongside other descriptive statistics. The table reveals the properties of the data in periods of crisis and calm or calm to make inferences on the behavior of the distribution.

There is a widespread between the minimum and maximum values in Nigeria and Ghana during the crisis period and a tight spread in South Africa, Tunisia, and the USA. On the other hand, during the calm period, the spread is minimal in all the countries except Nigeria which maintains a similar pattern to the crisis period, reflecting high volatility in market activities in Nigeria.

South Africa has the highest value of share price among the countries in both periods while Ghana has the lowest share price. It shows further that South Africa has a better stock market performance than other countries. In addition, the descriptive statistics reveal that Nigeria and Tunisia’s market indices are positively skewed in periods of crisis and stability. Conversely, South Africa and USA indices depict negative skewness in both periods. However, Ghana exhibits a mixed pattern – positive during the crisis and negative during the calm period.

Furthermore, the series identifies a negative correlation between Nigeria and the other countries except for South Africa. This implies that as the value of share prices increases or decreases in Nigeria, there is an inverse relationship between the value of stock prices in Ghana, Tunisia, and the USA. On the other hand, there is a direct relationship between stock prices in Nigeria and South Africa. This is evident in the sign of the correlation coefficients between the countries. Despite the signs, the results reveal a weak association between Nigeria and Ghana or Tunisia. However, there is a moderate correlation between the Nigerian stock market and that of the US during the crisis period, and a strong correlation in the post-crisis period, albeit negative.

For Nigeria and South Africa, during the crisis, the correlation is weak, but after the crisis, it is moderate. The positive relationship between the two stock markets is an evidence of moderate contagion in the markets. It also reveals that investors across borders in both markets have a penchant for risk. However, the other markets reveal a weak and negative contagion with Nigeria, i.e., no evidence of capital mobility across countries. It, therefore, shows that the investors in these markets are risk-averse, basing their investment decisions on prevailing economic circumstances. Such expectations are stoked by the perspective that during crisis periods, returns are low in the stock markets.

The co-skewness of the markets supports the nature of the association between the markets. In consonance with the correlation analysis, there is positive co-skewness between Nigeria and South Africa; however, it is negative between Nigeria and other countries. In summary, the result indicates that there is contagion between the Nigerian and South African stock markets, while there is none between Nigeria and the other countries. This result has implications for the African Continental Free Trade Area (AfCFTA). For trade to exist without barriers, then the stock market has
a great role to play especially concerning cross-border capital mobility. Even though the descriptive statistics suggest the absence of contagion, the subsequent section provides detailed empirical estimates and findings of the presence and nature of the contagion between Nigeria and other countries.

The results in Tables 3 and 4 present the posterior simulation evidence that is used in measuring the relationship between the selected stock markets. During the pre-crisis period, termed as regime 0, the following evidence emerge: firstly, the Ghanaian and Nigerian equity returns move in the opposite direction with SA’s, this is also the case between Nigeria and USA. This suggests that a gain in one market is a loss in another market. However, the stock markets in the USA, and Tunisia moves in the same direction as Ghana and SA. Also, the markets in Tunisia-USA and Tunisia-Nigeria were found to be positively correlated. From this, we can imply that a gain in either of the market is also a gain to another market. Secondly, the nature of the relationship seems to be weak as the magnitude of the correlation coefficient appeared to be very low less than 0.2 in all cases. The co-skewness evidence shows a negative sign between US-Ghana and USA-SA; and between Tunisia-SA and Tunisia-U.S.A The rest of the result shows the presence of positive co-skewness. This finding implies that there is a presence of fat tails among the selected stock returns, however, some of the markets comove negatively while some positively. The correlation and co-skewness evidence can further be confirmed with the covariance as it measures the extent of spillover across the markets. The covariance shows similarity in sign with correlation but is different with co-skewness.

| Markets  | Ghana | SA    | USA    | Tunisia | Nigeria |
|----------|-------|-------|--------|---------|---------|
| Crisis Period: 1st May 2016 to 31st December 2017 |
| Covariance | 311.5957 | –1.50586 | 0.45049 | 0.020892 | 0.13612 |
| | 0.869225 | 0.02817 | –0.05727 | 0.010159 | 0.349538 |
| Correlation | 1 | –0.1271 | 1 | 0.002 | 0.015408 |
| | 0.083289 | –0.16367 | 0.034335 | 1 |
| Co-skewness | 0.00853 | –0.00884 | 0.11417 | –0.00135 | 0.000172 |
| | –0.00172 | 0.166577 | 0.049467 | 0.197045 | 0.002641 |
| Mean | –0.04664 | 0.000433 | 0.028655 | 0.07213 | –0.03729 |
| Variance | 311.5957 | 0.45049 | 0.350298 | 0.25047 | 0.349538 |
| Skewness | 0.54 | 1.65 | –0.005 | 1.15 | –0.17982 | –1.57296 |
Furthermore, during the crisis period, that is regime 1, the evidence reveals a negative correlation for Ghana-SA, USA-Tunisia, and US-Nigeria while a positive correlation with other pairs of the relationship. The magnitude of the relationship appeared to be weak with a value less than 0.15 in any pair. This evidence is consistent with the pre-crisis period. The study also found mixed evidence in terms of the sign of co-skewness. For example, Ghana-SA, Ghana-US, Tunisia-SA, and Tunisia-Nigeria all appeared to comove negatively while the rest of the countries comove toward the right side of the distribution.

We compare the two periods, that is, the crisis and calm periods. The following rule of thumbs was set. Firstly, if there is a change in the sign of the statistic in question, it implies a change in direction between the two periods. For example, when a negative sign in the pre-crisis period change to a positive in a calm period, it implies that the markets move in the same direction and vice versa. Secondly, in terms of the magnitude, an increase in the magnitude from calm to crisis period indicates evidence of flight across stock markets. Now the question is, what is the flight meant for? This study further reveals if the flight between the stock markets exist, then what is the intention of the investors? Did they flee for safety, liquidity, or quality? Here, the study compares the correlation and co-skewness across the two regimes. From the evidence in Tables 3 and 4, we can see a decline in correlation during the crisis period. That is, the relationship is stronger during the calm period than it was during the crisis period. We can only establish evidence of an increase

Table 4  Posterior mean of switching parameter during calm period

| Markets       | Ghana       | SA          | US          | Tunisia     | Nigeria     | Nigeria     |
|---------------|-------------|-------------|-------------|-------------|-------------|-------------|
| **Calm Period: 1st January 2018 to 31st December 2019** |             |             |             |             |             |             |
| **Covariance** |             |             |             |             |             |             |
| Ghana         | 0.203838    |             |             |             |             |             |
| SA            | −0.01576    | 0.59829     |             |             |             |             |
| US            | 0.030126    | 0.096817    | 0.749423    |             |             |             |
| Tunisia       | 0.003588    | 0.012101    | 0.020723    | 0.055506    |             |             |
| Nigeria       | −0.00473    | −0.06039    | −0.00953    | 0.001855    | 1.063235    |             |
| **Correlation** |             |             |             |             |             |             |
| Ghana         | 1           |             |             |             |             |             |
| SA            | −0.04514    | 1           |             |             |             |             |
| US            | 0.077078    | 0.144588    | 1           |             |             |             |
| Tunisia       | 0.033734    | 0.066404    | 0.101605    | 1           |             |             |
| Nigeria       | −0.01015    | −0.07572    | −0.01068    | 0.007637    | 1           |             |
| **Co-skewness** |             |             |             |             |             |             |
| Ghana         | −0.19373    |             |             |             |             |             |
| SA            | 0.067617    | 0.974005    |             |             |             |             |
| US            | −0.58491    | −1.74011    | 0.14181     |             |             |             |
| Tunisia       | 0.139758    | −0.02119    | −0.05166    | 0.259979    |             |             |
| Nigeria       | 0.041204    | 0.211801    | 0.194664    | 0.995788    | 1.211323    | 1.063235    |
| Mean          | −0.04945    | −0.00797    | 0.149542    | 0.010812    | −0.07898    |             |
| Variance      | 0.203838    | 0.59829     | 0.749423    | 0.055506    | 1.063235    |             |
| Skewness      | 0.61        | −11.79      | −0.57       | 0.72        | −0.05       |             |
in a relationship during a crisis for Ghana-SA, Ghana-Nigeria, and Nigeria-U.S.A. This implies evidence of an increase in the relationship between the stated markets during the crisis period. There is an increase in the movement of capital investment in equities in either direction across the stock markets during the crisis period.

In terms of the direction of the relationship, the following changes were noticed. That is the pre-crisis period, the result reveals activities in Nigeria and Ghana markets move in the same direction. However, during the crisis period, the activities in the equities markets move in the opposite direction. This type of relationship was also established between Nigeria – SA, Tunisia, and U.S.A. For co-skewness, the following relationship emerges. In terms of signs, we noticed that co-skewness in most cases change to negative during the crisis period compared with the calm period. Here, theoretically, we expect three behaviors in terms of investors’ risk preferences. A change in sign from negative to positive during a crisis period indicates the risk-averse nature of investors. Also, if the sign changes from positive during the calm period to negative during the crisis period it is assumed that the investors are risk lovers. However, when there is no change in sign between crisis and calm period, the investors are risk-neutral. The evidence from our result reveals the evidence of risk lovers and risk-neutral investors. Furthermore, the sign of co-skewness changes the most for Nigeria.

Table 5 presents the contagion and structural break result. The table is divided into three panels: The contagion evidence is based on correlation, co-skewness and correlation and co-skewness. The second panel presents the test of structural breaks using mean, variance, skewness, and a combination of the three statistics and the last panel present the joint contagion and structural breaks.

| Tests                          | Methods | Ghana   | SA      | US      | Tunisia | Nigeria | ALL           |
|-------------------------------|---------|---------|---------|---------|---------|---------|---------------|
| **Contagion**                  |         |         |         |         |         |         |               |
| Correlation                   | P       | 0.2956  | 0.5829  | 0.3959  | 0.2836  | 1.000   | 0             |
| Co-skewness                   | BF      | –2.9133 | –1.9631 | 1.3785  | 2.0088  | 1.000   | –68.2764      |
| Corr&Skew                     | BF      | –1.7447 | –1.4471 | 2.1028  | 3.2397  | 1.000   | –59.4062      |
| **Structural Breaks**         |         |         |         |         |         |         |               |
| Mean                          | P       | 1       | 0.9471  | 0.9979  | 0.9991  | 0.9739  |               |
| Variance                      | BF      | 1       | 0.0942  | 0.001   | 1       | 0.0023  | 1             |
| Skewness                      | BF      | –0.4074 | 0.0900  | –0.3028 | 2.1650  | –2.0833 | –6.5946       |
| Mean, Variance & Skewness     | BF      | 1.0e03  | –2.7232 | –0.0011 | –0.0088 | –0.4932 | –0.0065       |
| **Joint Contagion**           |         |         |         |         |         |         |               |
| ALL                           | BF      | 1.0e +03 | –2.7276 | –0.0006 | –0.0045 | –0.4873 | –3.2220e +03  |

aStructural break test is reported but it is based on the summary statistics and not on the series as in the case of Bai and Perron (1998) or Zivot Andrews (1992). Therefore, dates are not available in this type of structural break test (see Baur 2003, Chan 2013)
From the evidence, the probability of correlation increasing during the crisis period is 50% between Nigeria-SA, 40% for Nigeria-USA, and 30% each between Nigeria-Ghana and Nigeria-Tunisia. This evidence suggests the presence of moderate contagion between Nigeria and SA during the crisis period and low contagion between Nigeria and the rest of the economies. This reveals that during the 2016 economic recession, investment in equities in Nigeria assumed a moderate flight to the SA equities market, but with a reduced flight to Ghana, USA and Tunisia. The co-skewness channel of contagion measures the asymmetric dependence of returns between two markets. Based on the result, it is evident that the correlation coefficient dominates that of bivariate co-skewness as the magnitude was found to be low. However, in the case of all the markets, we can’t reject the hypothesis of co-skewness contagion. The co-skewness evidence further reveals the presence of risk-averse investors between Nigeria-US and Nigeria-Tunisia and evidence of risk-loving investors between Nigeria-Ghana and Nigeria-SA. The joint correlation and co-skewness evidence show the absence of contagion across the markets, but the evidence favors the presence of joint contagion between all the markets.

The evidence for a structural break can be observed from the first three moments and their combinations. As discussed in the methodology section, if there is a structural break, the moments, especially the mean will decrease during the crisis period. This is because crisis lowers equity returns. From the result, it is evident that there is a structural break between Nigeria and all the countries during the crisis period. This is because the probability of a structural break in the mean is close to unity for all the relationships and even one between Nigeria and Ghana. This evidence is consistent for Ghana and Tunisia when co-skewness is used. However, the result fails to reject the hypothesis of a structural break for SA, USA, and Nigeria but the joint test between all the markets is in favor of a break. Combining the first three moments, the evidence rejects the presence of a break during the crisis period. The last panel in Table 5 presents evidence of joint contagion and structural breaks. The result reveals the absence of joint structural break and contagion for the individual markets and all the markets jointly.

Conclusions and policy implications

This study examined the contagion and structural breaks for some selected African economies, namely: Nigeria, Ghana, SA, Tunisia, and for the USA, a major African trading partner. For the analysis, two periods were considered: the crisis period, 1st May 2016 to 31st December 2017; and the calm period, 1st January 2018 to 31st December 2019. The choice of these periods was to account for the economic recession in Nigeria during the crisis period, and the subsequent relative recovery during the calm period. The assumption was: there was a capital flight to safety from equities in Nigeria to equities in selected emerging economies in Africa and/or the U.S.A Following the work of Chan et al. (2018), the study used regime-switching skew-normal model which is capable of measuring contagion and structural breaks between markets and across calm and crisis periods. The RSSN model was estimated using the Bayesian method.
From the results, the following evidence emerges: (i) There is a decline in correlation during the crisis period. That is, the relationship is higher during the calm period than it was during the crisis period. The study could only establish evidence of increased relationship during crisis for Ghana-SA, Ghana-Nigeria, and Nigeria-U.S.A. It is evident that there is an increase in the flow of equity capital in either direction across the stock markets during crisis period; (ii) In terms of the direction of the relationship, the following observations were noticed: In the pre-crisis period, the result reveals equity capital between Nigeria and Ghana markets moves in the same direction. However, during the crisis period, the markets move in opposite direction. This type of relationship was also established between Nigeria and SA, and Tunisia and US; (iii) In terms of risk preference of the investors across the selected economies, there is a presence of risk-averse and risk-loving investors; (iv) Further evidence suggests the presence of moderate contagion between Nigeria and SA during crisis period, and low contagion between Nigeria and the rest of the economies. This reveals that during the 2016 economic recession, capital in the Nigerian equities market experienced a moderate flight to SA, and a low flight to Ghana, US, and Tunisia; (v) The flight to safety that was confirmed between Nigeria and SA was found to be asymmetric which suggests non-linear relationship.

Based on the above findings, the study concludes the presence of moderate contagion between Nigeria and SA and the absence of contagion with the rest of the economies, suggesting flight of equity capital from Nigeria to the SA equities market for safety during the 2016 economic recession. Also, the study confirms the presence of structural breaks between crisis and calm periods, as the probability of the returns declining during the crisis period was found to be high. Therefore, the absence of contagion among African stock markets suggests that there is no significant economic cooperation and cross-border portfolio investment among the countries.

The policy implication of this research is underpinned on the imperativeness of the AfCFTA, which is aimed to encourage the free movement of goods and services, common customs unions, markets, and currency. With full implementation of AfCFTA, it is anticipated that cross-border activity would increase in the region, and with-it enhanced investment flow, thereby raising the degree of contagion among their stock markets. Thus, an understanding of the presence and nature of the contagion among African countries would help to shape the implementation of AfCFTA. If Nigeria, and indeed other African countries are to reap the greatest benefits from membership of AfCFTA, they would have to understand the contagion and its implication for capital flow within the region.

As there is evidence of risk aversion among investors between Nigeria-US and Nigeria-Tunisia, it is suggested that both countries should address the elements of those risks and pave ways for increased investment flow into their economies. In the case of investment flow from the US, Nigeria and other African countries would need to address the bottlenecks that discourage foreign investors by easing capital repatriation, stable exchange rate regime, now being achieved by harmonization of multiple foreign exchange segments, which is now being implemented by the CBN and an effective legal and regulatory framework. Nigeria should anticipate and take
advantage of the risk-loving appetite of the investors between Nigeria and Ghana and those between Nigeria and SA to encourage investment flow in Africa.

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