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Article

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TESTING FOR FINANCIAL SPILLOVERS IN CALM AND TURBULENT PERIODS

Shehu U.R. Aliyu¹, Nafiu B. Abdulsalam² and Sani Bawa³

Abstract

It has been established in the literature that volatility of stock returns exhibits complex properties of not only volatility clustering, but also long memory, regime change, and substantial outliers during turbulent and calm periods. Hence, this paper seeks to analyze volatility spillover, co-movements, independence and contagion in the Chinese, Japanese, Nigerian, South African, UK and US stock markets. Using a sample period spanning 2010M1 to 2018M12, the paper employs a state-space parameterization of Markov Regime Switching Model with skew-normal distribution and the Markov Chain Monte Carlo (MCMC) estimation procedure in the empirical analyses. The AMGARCH model with BEKK and DCC specifications was applied to detect presence of spillover and contagion effects from and across the financial markets as well. Posterior estimates show that the behavior of the series differ across two regimes; tranquil and crises. Specifically, market co-movements with the US Dow Jones rises during turbulence than during periods of tranquility particularly in the case of Nigeria NSE and the Johannesburg JSE. Furthermore, while the Nigeria's NSE and the JSE are entangled, the Japanese NIKKIE and the Chinese SHANGHAI show strong independence. We report evidence of bi-directional spillover transmission between the developed market (US market) and emerging markets (Nigeria and South African markets) to be asymmetrical and the likelihood for the markets to exhibit higher spillover from calm to turbulent regimes. Invariably, this validates the expectation that contagion is transmitted from the stronger markets to the weaker markets.

Keywords: Markov Switching, volatility, spillover effect, contagion effect, co-movement, stock markets

JEL Classification: C33; C53; G15

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1. INTRODUCTION

Market prices of risk assets, equities and other financial variables, vary over time as investors leverage on new information in their portfolio selection. This induces time variation in the volatility of assets' returns. Predicting swings in the stock market therefore has been the focus of many recent studies. Several studies, for instance, document that variability of returns tends to be higher during downside or "bear" markets than during upside or "bull" markets. Equally, market correlations, a closely related phenomenon, seems to vary over time and to rise particularly around episodes of financial distress which invariably characterize contagion effect. This implies a sustained propagation of shocks from the epicenter towards other financial markets (see: King and Wadhwani, 1990; Lee and Kim, 1993; Bua and Trecroci, 2016).

Knowledge of these configurations is quite useful not only to investors and regulators, but to policymakers as well. By forecasting bear markets, for instance, investors can exploit profitable opportunities by optimally timing their portfolios that could avail them higher returns by following a timing strategy rather than a buy-and-hold strategy (Shen, 2003). International investors could as well learn about the probability of having a crisis in the home market today following a negative shock to another market yesterday and could adjust their portfolio strategies to a changing structure of spillovers in different regimes (Bialkowski, Bohl and Serwa, 2006; Schwendener, 2010).

Assessing co-movement of financial markets and vulnerability of home capital markets to international crises is quite useful to regulators (Connolly & Wang, 2003; Bialkowski et al., 2006). Policy wise, predicting swings in stock market provides useful information about business cycles (Estrella and Mishkin, 1998). Evidence further suggests that widespread liquidity problems are symptoms of credit crunches in financial markets during bear market periods (Bernanke and Lown, 1991); thus, monetary authorities could as well leverage on information on booms and bursts to achieve their mandate of maintaining sound financial stability (Rigobon and Sack, 2003).

Literature is replete with evidences that regime shifts in financial time series cannot be modelled implicitly using simple linear time series model. For instance, Schwendener (2010) states that the phenomenon of volatility clustering characterized by the well-known high persistence of financial shocks, leads to structural changes in the variance process. He further noted that single-regime approaches, like GARCH, and its forerunner ARCH, introduced by Engle (1982), cannot capture (due to inflexibility of the GARCH parameters) the phenomenon of the volatility clustering which invariably is characterized by structural breaks in the variance process (Gray, 1996). Besides, GARCH model underestimates the variance in times of crises, while it overestimates them in low volatility times.

Consequently, a nonlinear time series model is typically designed to accommodate this nonlinear feature in the data. Further, models with recurring regimes have been used to characterize bull and bear markets, calm versus turbulent markets, and recession and expansion periods (Ang and Timmermann 2011). First, the idea of regime change is both natural and intuitive. The pioneering application of regime-switching model was by Hamilton (1989), to capture business cycles; recessions and expansions, and the regimes naturally captured cycles of economic activity around a long-term trend. Others include, Turner, Startz, and Nelson (1989), Schwert (1989), Nishiyama (1998), Ramchand and Susmel (1998), Forbes and Rigobon (2002) and Guidolin and Timmermann (2006). Therefore, regime-switching models offer more flexible and compact structure with the ability to capture structural breaks of time series within a single, unified model (Schwendener, 2010). Investigation by Bua and Trecroci (2016) found that international equity correlations display a clear tendency to grow and remain high around notable episodes of high volatility and financial turbulence, such as 1987, 1997-1998, 2000-2002 and 2008 to 2010. Furthermore, macroeconomic downturns also tend to accompany the increases in correlations, and the US recessions always lead to slowdowns in the rest of the countries around the world.

Against this background, this paper seeks to test for financial spillover effects during turbulent and calm periods across stock markets in the United States, United Kingdom, Japan, China, South Africa and Nigeria. The paper also investigates the patterns of co-movements, contagion effects, dependence and independence among the stock markets. The rest of the paper is organized as follows: Section II reviews the literature and theoretical issues while section III explains the analytical model, estimation methods and diagnostics. Section IV analyses data characteristics using basic statistics, presents empirical results, interpretations and diagnostics. Section V presents the conclusion and key recommendations of the paper.

2. LITERATURE AND THEORETICAL ISSUES

International investment flows and capital movements characterized by financial integration-cum-globalization continue to shape the global financial landscape. As a result, this dictates the pattern of correlations among assets denominated in different currencies exchanged in geographically-separated markets. Often, volatility in one market reacts to shocks in other markets as a result of increased financial integration. Thus, the patterns of stock returns frequently exhibit evidence of non-linearities. To capture this, the Markov-switching model provides a framework in which regimes are associated with various combinations of low and high volatility in each country. For instance, evidences in the literature show high persistence and heteroskedasticity of stock market returns as well as volatility switches at business-cycle frequencies (Schwert, 1989; Ramchand and Susmel, 1998; Naeini and Fatahi, 2012; and Viskovic et al., 2014). Common phenomena identified in the literature on this are the volatility clustering, spillovers, co-movements, contagion, market dependence and independence (see Mandelbrot, 1963; Cont, 2001; Connolly & Wang, 2003; Edwards and Susmel, 2003; Gebka and Serwa, 2006; Diebold and Yilmaz, 2008 and Schwendener, 2010).

A plethora of studies have assessed the spillover effects of shocks from one market to another; usually one country is *ex ante* considered the *originator* of the crisis (dominant market) and the correlation coefficient is made dependent on the state of such originator country (see Gallo and Ortranto, 2007; Forbes, 2012; Bua and Trecroci, 2016; Yang, Lee and Yao, 2017). Contagion is when correlations among international stock markets increase in volatile times (e.g. market crashes) and obtain extremely high positive values. It drives the correlation coefficient to unity and reduces the potential of portfolio diversification at the time investors needed it most (Gulko, 2002). This could be due to *monsoonal effects*, that is, when coherence of the financial markets with an exogenous event triggers several countries at the same time into crises, otherwise *spillover effects*. That is, when there are interdependencies among national economies or *true contagion* effects, when the transmission of crises cannot be interpreted by changes in macroeconomic fundamentals (Kaminsky and Reinhart, 2000; and Tschabold, 2002).

Forbes and Rigobon (2002) discover that the shock originating from Hong Kong in October 1997 had no significant increase in the correlation coefficients of the other main Asian markets. The conclusion is that the series analyzed are not subject enough to form spillover from Hong Kong, but rather the markets considered exhibit interdependence. Further, Gallo and Ortranto (2007) estimate MMS and MCMS models with 4 x 4 transition probability matrices and with 2 x 2 states, that is, stable and turbulent regimes, using five Asian stock markets (Hong Kong, Singapore, Korea, Thailand and Malaysia). The aim is to detect spillover, independence, interdependence and co-movements across the markets. The assumption that markets should be measured in their relationships to Hong Kong made by the authors is a reasonable one. The results show plausible market characterizations over the long run with a spillover effect from the Hong Kong market to both the Korean and Thailand markets, evidence of interdependence for the Malaysia/Hong Kong markets and co-movement with the Singaporean market.

In the United States, Marcucci (2005) assesses the ability of different GARCH models, including a Markov Regime-Switching GARCH model, to forecast financial time series volatility using the US stock

market data. Empirical results indicate that Markov Regime-Switching GARCH models outperform the standard GARCH models in forecasting volatility at shorter horizons. However, the standard GARCH models outperform the MRS-GARCH models at longer horizons. The author concludes that accounting for regime shifts from turbulent regime to a tranquil one together with the inclusion of GARCH effects gives better results. Similarly, Naeini and Fatahi (2012) using both the standard GARCH and regime-switching GARCH models in the Tehran Stock market attest to the superiority of the regime-switching GARCH models over the standard GARCH models on forecasting performance. Furthermore, Guesni et al., (2013) posit that the application of MRS-GARCH allows them to identify regime shifts in twelve OECD stock markets during the global financial crises.

Meanwhile, Schwendener (2010) develops a Markovian regime-switching model based on a multiple regression framework to describe the dynamics of financial markets using an asset universe of eleven worldwide assets; bonds and stocks from the United States, United Kingdom, Europe, Emerging Markets, China, Japan and Switzerland. The findings, among others, show that the CHs and the EUs depend with a small but significant positive factor loading on the USD-factor. The European asset categories (EUB and EUs) depend on the EUR-factor, likewise the JPY-factor describes the dynamics of the Japanese asset categories (JPb and JPs). Of great interest, the Swiss real estate asset is almost exclusively driven by its factor which confirms the need for diversification. Finally, the emerging market stocks showed, especially in the years 2007 and 2008, high sensitivity while the JPs possessed, on average, the lowest beta of all equity markets over the last ten years.

Jung and Maderitsch (2014) investigate volatility transmission between the stock markets in Hong Kong, Europe and the United States for the period January 2000 – September 2011. Analyzing the structural stability of volatility spillovers from foreign markets into domestic markets, the study found the dynamics of volatility spillovers to be unstable and highly time-varying. The results further reveal a strong and sudden upward shifts in volatility spillovers in all markets during the global financial crisis. Investigating the role of structural breaks and conditional heteroskedasticity in the realized volatilities further, the study found that structural breaks only had a minor impact on volatility spillovers, while conditional heteroscedasticity tend to have a major impact.

Charisis (2015) examines the existence of market contagion among the European sovereign debt crisis. The study characterized crisis into two sub periods; the pre-crisis period of the European crisis period marked by U.S crisis and the European crisis period. The sample contain only the mostly severely affected countries by the crisis--Greece, Ireland, Portugal, Italy, and Spain, while Germany and United States were included as benchmark countries. The variables used are the 10-year government bonds and stock price index. Using 3 tests; the Forbes and Rigobon test (2002), co-skewness test developed by Fry, Martin and Tang (2010) and the cokurtosis test developed by Hsiao (2012), results reveal that market contagion was not limited to the sample countries but other countries in the zone at varying magnitude. Moreover, the subsistence of contagion was captured more efficiently through tests that included higher order moments.

Investigating dependence structure among various financial market indices for risk management, asset pricing and portfolio optimization was the focus of the study by Wuyi, Zhu, Wu and Miao (2016). The paper employs a Markov regime-switching quantile regression model where the parameters were estimated using the Maximum Likelihood estimation (MLE) method to detect the degree of financial crisis contagion between the US and some European Union countries during the period of sub-prime crisis. Their major finding indicates that the interdependence between the US and EU financial markets dramatically increases during periods of the crises.

Analysis of the nature of shocks transmission across international equity markets (USA, Japan, UK, France, Germany, and Canada) was carried out by Bua and Trecroci (2016). The paper evaluates shifts and co-movements during business-cycle using an “identification through heteroskedasticity”

methodology. The paper reports three key findings regarding co-movement amongst returns. Firstly, persistence of high-volatility across all the indices coincide with macroeconomic slowdowns. Secondly, an observed rise in the responses of international stock returns to common shocks during turbulent periods. Thirdly, since the late 1990s, returns have been hit more often by high-volatility common shocks due to larger and more persistent macroeconomic disturbances.

Yang et al., (2017) analyze volatility co-movement and contagion in the stock markets of four countries (China, Japan, Korea, and Taiwan) in East Asia, which are closely connected with each other geographically and economically in terms of short-term and long-term perspectives. Using the Bivariate Markov Switching Multifractal (BMSM) volatility model, the results show that China has no significant correlation with the other three countries which suggests that the Chinese stock market is an isolated or segmented market. In addition, the influence of financial crisis on the East Asian countries varies, depending on the country, with Korea and Taiwan as the most vulnerable to external shocks compared to China and Japan.

Ardia et al., (2018) find that MSR-GARCH models deliver better Value-at-Risk, expected shortfall and left-tail distribution forecasts than the single regime counterparts, especially for stock returns data. They recommended that risk managers should extend their GARCH-type models with Markov-switching specifications in the case of investments in equities. In the same vein, Lolea and Vilcu (2018) evaluate both models using data for the Romanian stock market. Findings show that while the in-sample analysis indicates the superiority of the asymmetric GARCH models, the out-of-sample forecasting reveals that the regime-switching models were superior particularly, for short time horizon, and that they greatly help in improving the quality of volatility forecasts.

Bala and Takimoto (2017) examine volatility spillovers of stock returns across markets in developing and developed countries by applying variants of MGARCH models and found strong correlations in the latter markets, thus implying more interactions than in the former, that is, emerging markets. Also, volatility spillovers in the stock markets are greater in comparison to the cross-volatility spillovers especially for emerging markets. This implies that the emerging markets are less efficient than the developed markets as the impact of any shock in these markets takes greater time to dissipate. The authors suggested the DCC-with-skewed-t density model for capturing the volatility dynamics if fat tails and skewness is present in the data.

Examining the level of risk associated with spillover effect between the US and the rest of the G7 stock markets – Canada, France, Germany, Japan, Italy and UK – using time-varying copula models with Markov switching was conducted by Ji, Liu, Cunado, and Gupta (2018). The study covers the period January 1915 to February 2017. Findings show that the dependence structure varies with time and exhibits distinct high and low dependence regimes. In addition, the study found the existence of risk spillover between the US stock market and the remaining G7 stock markets. The result suggests that any negative shock affecting one of the stock markets rapidly affects other markets and, thus increases global systemic risk. Positive shock, however, does not rapidly spread among the different stock markets. Furthermore, negative shock originating from the other six countries tends to have more negative effects on the US stock market than the one originating from the US on others.

In a recent study, de Oliveira et al., (2018) evaluate spillover effects and transmission of volatility to and from the Brazil stock market during the volatile period of 2014-2016. Using the MGARCH-BEKK along with DCC and t-Copulas models, the authors found that the main source of volatility to Brazil are US monetary policy and rebalancing of portfolios. Furthermore, Brazil also induces volatility to commodity markets and US bonds market plays the role of an intermediary of these markets. Ozdemir and Vurur (2019) conduct variance causality test and found that there is a bidirectional volatility spillover between the US S&P500 index and the Turkish's BIST100 index. When the return spillover between the markets was examined, a one-way spillover from the S&P500 index to the BIST100 index emerged.

In addition, the Diagonal BEKK model results show that each market is affected by its own news (unexpected shocks) and volatility. Also, the volatility is persistent for both markets. These findings show that the US S&P500 index and the Turkish's BIST100 index interact with each other.

The main motivation for the paper lies in the application of Markov regime-switching framework that allows capturing fat tails as well as other empirical properties of asset returns like contagion, decoupling and stochastic volatilities. It is evident in the literature that the presence of fat tail phenomenon vitiates the assumption that empirical distribution of financial time series is normal, that is, '*iid*' distributed. In this regard, no evidence of application of Markov regime-switching with skew normal distribution in detecting spillover in financial markets incorporating Nigeria, so far, is documented in the literature. The paper, in addition, applies asymmetric multivariate generalized autoregressive conditional heteroskedasticity model (AMGARCH) using both the Baba, Engle, Kraft and Krooner (BEKK) model and the Tse-Tsui Dynamic Conditional Correlation (DCC) model. This underscores the need for the investigation.

3. METHODOLOGY

3.1 Introduction

This section reviews and highlights the quantitative tools of data analysis used for the empirical investigation in the paper. It discusses the techniques for exploring the data, the preliminary analysis, specification of the empirical models and diagnostic tests employed. Additionally, the section scans the data generating process in a Bayesian framework of analysis as well as frequentist methods of data analysis.

3.2 Bayesian Empirical Models

3.2.1 Markov-Switching with Skew-normal Distribution

Following Sahu and Zhigljavsky (2003) and Chan, Henderson, Parmeter, and Tobias (2017), the latent variable is specified as:

$$x_t = \xi + \varphi Z_t + \zeta_t \dots \dots \dots 3.1$$

$$\zeta_t \sim iid N(0, \Sigma), \dots \dots \dots 3.2$$

$$Z_t \sim iid N(c1_m, I_m) 1(Z_{jt} > c, j = 1, \dots, m) \dots \dots \dots 3.3$$

Where $x_t = (x_{1t}, \dots, x_{kt})'$ is a k -dimensional random vector with $t = 1, \dots, T$, ξ is a $k \times 1$ vector of constants, φ is an $k \times k$ skewness co-skewness matrix, $Z_t = (Z_{1t}, \dots, Z_{kt})$ is a k -dimensional random vector, ζ_t is an $k \times 1$ vector of innovations, Σ is an $k \times k$ variance-covariance matrix, 1_m is a $k \times 1$ columns of ones, I_m is the identity matrix, and $1(\cdot)$ is a scalar indicator function which takes a value of 1 if all Z_{jt} are greater than c and 0 otherwise.

The marginal probability density function of x_t is:

$$f_{SN}(x_t; \xi, \Sigma, \varphi) = \frac{2^k}{\det(\Sigma + \varphi^2)^{1/2}} f_N \left[\left((\Sigma + \varphi^2)^{-1/2} \right) (x_t - \xi) \right] \Pr(V > 0) \dots \dots \dots 3.4$$

$$V \sim [\varphi(\Sigma + \varphi^2)^{-1}(x_t - \xi), I_m - (\Sigma + \varphi^2)^{-1}\varphi] \dots \dots \dots 3.5$$

With assumption of non-normality in the vector of innovation, we can allow the model parameters to vary across the regime so that we can reparametrize equation 3.1 as:

$$x_t = \xi_{s_t} + \varphi_{s_t} Z_t + \zeta_t \dots \dots \dots 3.6$$

$$\zeta_t \sim iid N(0, \Sigma_{s_t}), \dots \dots \dots 3.7$$

$$Z_t \sim iid N(c1_m, I_m) 1(Z_{jt} > c, j = 1, \dots, m) \dots \dots \dots 3.8$$

The regime s_t at time t is a discrete variable with two outcomes that are either 0 or 1. Thus, we can define the regime as: $s_t \in \{0, 1\}$. This can be explained as;

$$s_t = \begin{cases} 0 & \text{if the regime is in normal or calm period} \\ 1 & \text{if the regime is in turbulence period} \end{cases} \dots \dots \dots 3.9$$

This suggest that the mean, ξ_{s_t} , co-skewness, φ_{s_t} , and the error cross-variance, Σ_{s_t} in equation 3.6 to 3.8 to change in regime $s_t = 1$ compared to regime $s_t = 0$.

On a final note, we can compactly rewrite equations 3.6 to 3.8 as:

$$x_t = Y_t \alpha_{s_t} + \zeta_t \dots \dots \dots 3.10$$

$$\zeta_t \sim iid N(0, \Sigma_{s_t}) \dots \dots \dots 3.11$$

Where:

$$Y_t = (I_m, I_m \otimes Z_t'), \quad \alpha_{s_t} = (\xi_{s_t}', \gamma_{s_t}'), \quad \gamma_{s_t} = vec(\varphi_{s_t}')$$

The process of transitioning from one regime to the next, that is from calm market period to turbulence period is defined in terms of Markovian process as:

$$P_r(s_t = 1 | s_{t-1} = i) = p_{it} \dots \dots \dots 3.12$$

$i = 0 \text{ and } 1$

Where p_{it} is the time-varying transition probability and by collecting the parameters of the model, we can define them as:

$$\emptyset = [\alpha_0, \alpha_1, \Sigma_0, \Sigma_1] \dots \dots \dots 3.13$$

The state-dependent correlation coefficient for two market returns, ρ_{ij, s_t} , can also be expressed as:

$$\rho_{ij, s_t} = \frac{\Sigma_{ij, s_t}}{\sqrt{\Sigma_{ii, s_t}} \sqrt{\Sigma_{jj, s_t}}}, s_t = 0, 1 \dots \dots \dots 3.14$$

3.2.2 Markov Chain Monte Carlo (MCMC) Estimation Strategy

The likelihood function used in building up the posterior distribution is given as:

$$f(x|Z, \emptyset, s) = (2\pi)^{-\frac{kT}{2}} \prod_{t=1}^T |\Sigma_{s_t}|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2} \sum_{t=1}^T [x_t - Y_t \alpha_{s_t}]' \Sigma_{s_t}^{-1} [x_t - Y_t \alpha_{s_t}] \right\} \dots 3.15$$

Where: x, Z, \emptyset and s are stacked expressions.

The normal-inverse priors used are specified as:

$$\alpha_{s_t} \sim N(\alpha^*, V_{\alpha}^*), \dots \dots \dots 3.16$$

$$\Sigma_{s_t} \sim IW(\omega_{\Sigma}^*, S_{\Sigma}^*) \dots \dots \dots 3.17$$

$$\Pr(s_t = 1 | s_{t-1} = i) = p_{it}, \quad \Pr(s_t = 0 | s_{t-1} = i) = 1 - p_{it} \dots \dots \dots 3.18$$

Combining equation 3.15 with 3.16 and 3.17, we obtain the posterior distribution given as:

$$\pi(\emptyset, Z, s | x) \propto f(x | Z(\emptyset, s)) f(Z) f(s | (\emptyset)) \pi(\emptyset) \dots \dots \dots 3.19$$

3.2.3 Tests for Spillover in Calm and Turbulence Regimes

To test for spillover of shock across the market, we compute spillovers at two levels. At the first level, we compute correlation spillover by proposing that:

$$p_{ij, s_{t=1}} > p_{ij, s_{t=0}}, \quad \text{for } i \neq j \dots \dots \dots 3.20$$

The hypothesis is based on the assumption that the correlation parameters will naturally increase as long as the markets closely move together during crisis. Therefore, we test the following hypothesis:

$$H_0: p_{ij, s_{t=1}} - p_{ij, s_{t=0}} = 0 \dots \dots \dots 3.21$$

$$H_a: p_{ij, s_{t=1}} - p_{ij, s_{t=0}} > 0 \text{ for } i \neq j \forall i \text{ and } j \dots \dots \dots 3.22$$

We use the MCMC to draw and calculate the proportion of correlation which satisfy the condition. Additionally, at the second level, we test for co-skewness and spillover by formulating and testing the hypothesis that:

$$H_0: \gamma_{ij, s_{t=0}} - \gamma_{ij, s_{t=1}} = 0, \quad \text{for } i = j \dots \dots \dots 3.23$$

$$H_a: \gamma_{ij, s_{t=0}} - \gamma_{ij, s_{t=1}} \neq 0, \quad \text{for } i \neq j \dots \dots \dots 3.24$$

The test is meant to investigate the asymmetric spillover dependence of returns *i* and *j* in regime $s_t = 0$ (calm) compared with regime $s_t = 1$ (turbulent). Again, we run MCMC to draw and compute the proportion of co-skewness that satisfies the inequality restriction.

3.3 Data metrics and Variables Measurement

The data for the analysis is time series, and mixed frequency approach was used, that is, both quarterly and monthly series covering the period from 2010M1 to 2018M12. The data generating process (DGP) is inherently stationary, following standard literature on Bayesian data analysis (see Stock and Watson, 2005a, 2005b; Bai and Ng 2010, 2013). The Bayesian econometric models allow generation posterior and prior distributions that are product of the likelihood function. The posterior distributions are used for the estimation of the parameters while in the frequentist econometric model, parameters come from the likelihood function.

The returns series are obtained across the leading markets in the US, Europe, Asia and the African continents. Thus, our sample generates returns series from the Dow Jones market in the US, FTSE in the United Kingdom, NIKKEI 225 in Japan and SHANGHAI COMPOSITE for the Chinese market. In Africa, JSE and NSE represent market returns for South Africa and Nigeria, respectively.

IV. EMPIRICAL RESULTS

In this section, the results of the models specified are presented. In particular, we present the Markov regime switching model multivariate estimated results and evaluate parameters based on covariance, correlation and co-skewness. Furthermore, structural breaks in the mean, variances and skewness of the asset returns across the markets are also evaluated along with the diagnostic tests.

4.1 Some Exploratory Data Analysis

To investigate the information contained in our six stock returns, we produce summary statistics with higher order moments and co-movements. Intuitively, we characterize two periods of analysis based on major global event, that is, the 2007 US mortgage crisis, which *ex-ante* singles out the US as the originator country (see: Forbes, 2012; Bua and Trecroci, 2016; Yang et al., 2017). We assume the period from January 2000 to March 2007 to be regime one which is crisis free and hence ‘*Calm Regime*’ while the period January 2008 to March 2018 to be regime two which is crisis period and hence ‘*Turbulent Regime*’.

We compute the continuously compounded return due to its attractive statistical properties such as stationarity, ergodicity and the fact that returns across markets can be more easily compared as well as being unit/scale free (see Campbell and Wasley, 1997 and Tsay, 2002). The weekly percentage returns are calculated as

$$r_t = 100 \times (\ln P_t - \ln P_{t-1})$$

where r_t is index return, P_t is the stock index at time t and P_{t-1} is the stock index at time $t-1$.

Table 1: Stock Returns During Calm Regime (2000-2007)

Statistics	NG	SA	JP	CH	UK	US
Mean	0.065	0.107	0.090	0.043	0.056	0.038
Minimum	-4.037	-4.931	-5.262	-3.364	-3.765	-3.349
Maximum	3.698	4.492	5.015	3.069	4.982	2.069
Std. dev.	0.925	1.057	1.101	0.875	0.981	0.634
Skewness	-0.234	-0.564	-0.371	-0.279	-0.642	-0.333
Correlation	0.413	0.346	0.178	0.384	0.421	
Co-skewness	-0.113	-0.157	-0.151	-0.151	-0.159	

Source: Authors computations based on market returns of United States, United Kingdom, China, Japan, Nigeria and South Africa.

Table 2: Stock Returns During Turbulent Regime (2008-2018)

Statistics	NG	SA	JP	CH	UK	US
Mean	-0.025	-0.017	-0.010	-0.013	-0.016	-0.028
Minimum	-5.037	-5.991	-5.822	-3.984	-3.825	-4.489
Maximum	8.698	5.472	5.585	3.549	4.992	3.759
Std. dev.	2.924	2.455	1.931	2.615	2.284	1.464
Skewness	-0.924	-0.984	-0.671	-0.349	-0.762	-0.913
Correlation	0.593	0.687	0.718	0.884	0.531	
Co-skewness	-0.413	-0.237	-0.871	-0.871	-0.239	

Source: Authors computations based on market returns of United States, United Kingdom, China, Japan, Nigeria and South Africa.

The summary statistics in Tables 1 and 2 show that pairing US and other country’s equity returns produce information relating to the co-movements of global financial market. There is strong evidence

of nonlinear co-movements among the equities of the countries from the regime. The mean values of the returns in the calm regime are all positive but negative in the turbulence regime. Additionally, the turbulent regime is more volatile in view of larger minimum and maximum values compared with tranquil period. The measure of stock market volatility is comparatively bigger indicating larger shocks during the turbulence period.

Furthermore, comparing the size of co-movements across the two different regimes reveals evidence of correlations and co-skewness in the turbulent period in contrast to the calm period. This indicates that there are contagions and spillovers across the six stock markets. It also implies spillover effect from the US to CH and JP leading with correlation values of 0.884 and 0.718, respectively. The UK and NG leads with lower correlations of 0.531 and 0.593, respectively. Co-skewness remains consistently negative across both regimes but peaked in the turbulent regime in CH and JP. These suggest both the intensity and direction of non-normal distribution.

Next is an investigation of evidence of fat tails in the distribution of the asset returns in the markets. Fat and heavy tails are also indications of non-linear co-movements in the series and these can be observed from plots of probability density functions of the asset returns. These are presented in Figures 1-6, as follows:

Figure 1: Probability Density of US Series

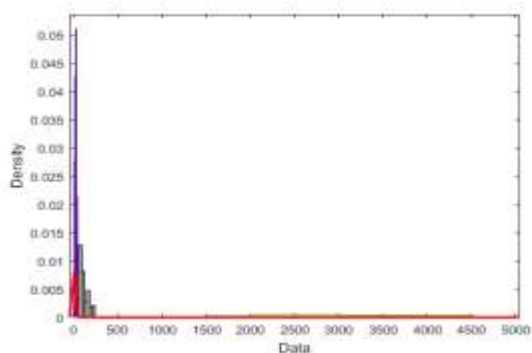


Figure 2: Probability Density of UK Series

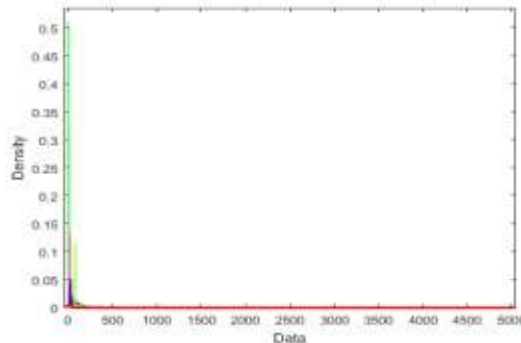


Figure 3: Probability Density of JP Series

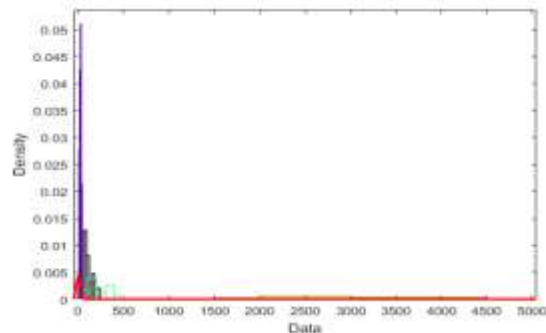


Figure 4: Probability Density of CH Series

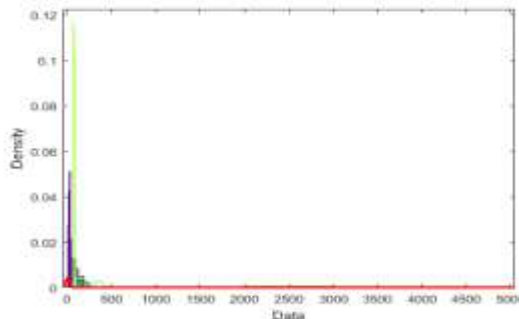
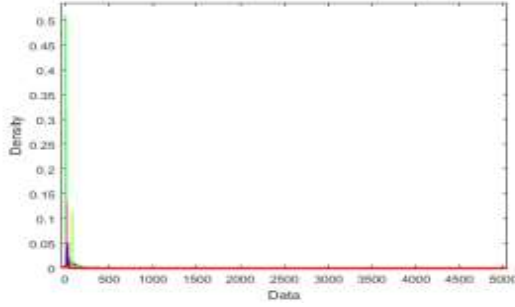
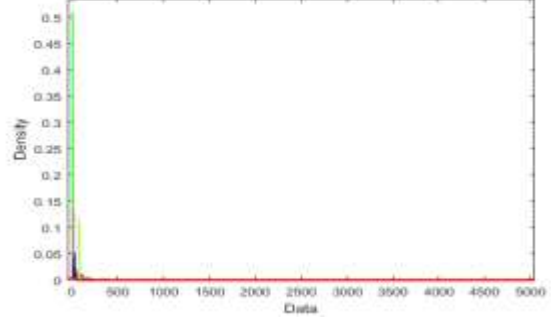
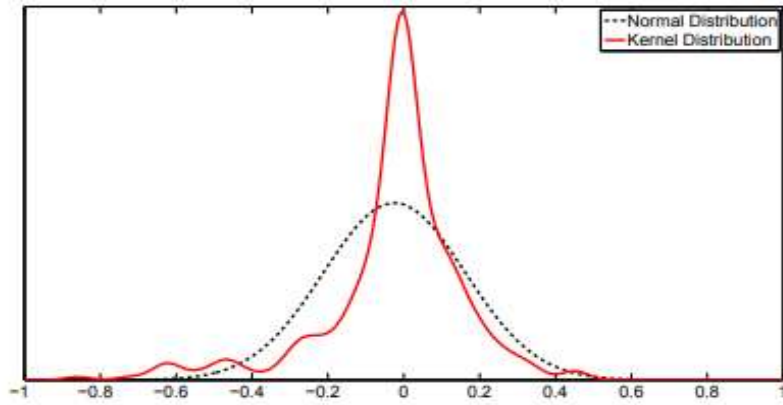


Figure 5: Probability Density of SA Series**Figure 6: Probability Density of NG Series**

A distribution with fat tails enables the accommodation of the likelihood of large positive and negative shocks impacting the economy and, hence, normal distribution is inappropriate as it tends to undervalue the rare events continuously (Cont, 2001). Additionally, the generated Kernel density of the market returns visualizes the features of fat-tail, extreme values, time-varying volatility and nonlinearities. Thus, the returns series of the six markets, therefore, exhibit a clear case of non-normality and, necessitate the use of a model that could take these dynamics into account.

**Figure 7: Joint Kernel Density of the Equity Returns**

Moreover, we produce the joint distribution of the six equity returns in Figure 7 and superimpose the Kernel density on the fitted normal distribution. This demonstrates a clear deviation between the joint distributions and re-echoes the evidence of nonlinearities in our series.

Using the 'ggplot2' by Wickham (2010), we generate probability density of the standardized returns for the two regimes-calm and turbulent regimes. These are presented in Figures A.1 and A.2 and Figures A.3 and A.4, respectively (see Appendix I). In Figure A.1, fat-tails of the UK, US and JP markets are depicted also in Appendix I, during the calm period, respectively. It can be seen that the dashed line which measure the amount of deviation and non-normality in the distribution of the series for the UK is marginal whereas the dashed lines for the US and JP are far away from the density of the series. These suggest high incidence of fat-tails especially for JP series. Corresponding to the tranquil regime, Figure A.2 shows that the size of non-normality increases significantly during the turbulent regime because the deviation becomes far away from the density of the series in all the three markets. This indicates that the series exhibit more evidence of nonlinearities, non-normality, fat-tails and shifts during the turbulent regime than during the calm regime.

Similarly, Figures A.3 and A.4 depict the size of deviation and non-normality for CH, SA and NG for calm and turbulent regimes, respectively. Evidently, the size of deviations during the calm and turbulent regimes are remarkably different than in the preceding three markets--UK, US and JP. This time around, there are more evidences of fatter tails in the tranquil regime than in the turbulent regime. Thus, it is clear based on the exploratory data analysis that the behavior of the market returns is characterized by the presence of fat tails and nonlinearities across the calm and turbulent regimes.

Confirmatory tests using ten (10) test statistics by Öner and Kocakoç (2017) confirm that a total of eight (8) test statistics in the calm regimes and all the ten (10) test statistics in the turbulent regime reject the null hypothesis of normality in the stock returns series. See Appendix II Table A.1 for the results. The tests, thus, corroborate the earlier results that non-normality is more evident in the crisis period than in the tranquil period. Finally, Figure A.5, Appendix III depicts different forms of contour plot of the probability density function of the stock returns across different market returns. Significantly, the plots show asymmetries in the skewness as well as in the co-skewness that translate to highly non-linear series across the markets.

4.2 Model Estimation

In this section, we estimate the Markov Regime-Switching Skew Normal (MRSSN) model and interpret the parameters associated with co-skewness, correlation and spillovers. The objective is to produce empirical evidence with regime shift in mean, volatility (variance) and correlation in the two distinct periods, that is, calm and turbulent, otherwise bear and bull markets.

Tables 3 and 4 present our estimation results/parameters in terms of the probability that the model is in a particular regime, $s_t = \{0,1\}$. Looking at the estimates in the Tables, we can see that the coefficients significantly change over the two regimes. Table 3 produces estimates when we set $s_t = 0$, calm period, while Table 4 yields parameter values assuming that $s_t = 1$, turbulent period. Evidently, spillover through correlation and co-skewness appear to have changed in sizes and signs. The correlation of pairs of returns becomes larger for several markets during turbulent regime than during calm regime. For example, pairing the US market with the rest of the markets, we can say that the co-movements across the markets have increased. During the pre-crisis regime, the correlation between the NSE and Dow Jones is 0.419 but it later increased to 0.659. Equally, the correlation between JSE and Dow Jones increased from 0.427 to 0.817. Similar pattern is observed in the remaining markets. Comparing the Asian markets, NIKKEI and SHANGAI returns reveals lower co-movement in their correlation, that is, from 0.298 in calm regime to 0.548 in turbulent regime while the African market correlation, NG and SA, shows stronger co-movement of 0.371 and 0.721 over the two regimes.

Table 3: Bayesian switching parameters (posterior means estimates) Calm Regime ($s_t = 0$)

Parameters	Markets	<i>NG</i>	<i>SA</i>	<i>JP</i>	<i>CH</i>	<i>UK</i>	<i>US</i>
Covariance ($\Sigma_{ij,0}$)	NG						
	SA	0.299					
	JP	0.150	0.193				
	CH	0.288	0.246	0.148			
	UK	0.231	0.342	0.543	0.876		
	US	0.109	0.067	-0.013	0.089	0.365	

Correlation ($\rho_{ij,0}$)	NG						
	SA	0.371					
	JP	0.520		0.393			
	CH	0.728		0.646	0.298		
	UK	0.421		0.342	0.453	0.936	
	US	0.419		0.427	-0.323	0.089	0.455

Co-skewness ($\psi_{ij,0}$)	NG						
	SA	-0.431					
	JP	-0.327		-0.393			
	CH	-0.528		-0.646	-0.298		
	UK	-0.561		-0.342	-0.453	-0.936	
	US	-0.419		-0.427	-0.423	-0.089	-0.455

Mean ($\mu_{i=0}$)		0.044		0.079	0.066	0.025	0.031
0.873							
Variance ($\Sigma_{ii,0}$)		0.399		0.469	0.525	0.368	0.367
0.543							
Skewness ($\psi_{ii,0}$)		-0.586		-0.761	-0.880	-0.488	-0.072
-0.921							

Table 4: Bayesian switching parameters (posterior means estimates) Turbulent Regime ($s_t = 1$)

Parameters	Markets	<i>NG</i>	<i>SA</i>	<i>JP</i>	<i>CH</i>
<i>UK</i>	<i>US</i>				
Covariance ($\Sigma_{ij,1}$)	NG				
	SA	2.499			
	JP	3.156	4.653		
	CH	4.018	1.546	2.748	
	UK	6.631	1.972	5.752	0.876
	US	3.109	5.467	6.095	0.089

Correlation ($\rho_{ij,1}$)	NG				
	SA	0.721			

	JP	0.650	0.683			
	CH	0.832	0.946	0.548		
	UK	0.721	0.642	0.763	0.953	
	US	0.659	0.817	-0.433	0.259	0.526

Co-skewness ($\psi_{ij,1}$)	NG					
	SA	-0.118				
	JP	-0.127	-0.193			
	CH	-0.218	-0.416	-0.098		
	UK	-0.321	-0.342	-0.153	-0.236	-0.143
	US	0.196	0.217	-0.423	-0.089	0.155

Mean ($\mu_{i=1}$)		-0.144	-0.279	-0.466	-0.125	-0.193
-0.119						
Variance ($\Sigma_{ii,1}$)		0.529	0.695	0.725	0.608	0.867
0.943						
Skewness ($\psi_{ii,1}$)		-0.586	-0.761	-0.880	-0.488	-0.072
-0.921						

Of serious implications is the co-skewness across the pairs of market returns. Generally, the results reveal that the co-skewness indices are consistently negative in the calm period and become less negative, albeit positive in some selected markets from calm to turbulent regimes. For instance, pairing US with NG, co-skewness coefficient is -0.419 during the calm period but changed to 0.196 during the turbulent period. This implies that investors prefer to invest in portfolios that are less risky in the latter regime. The same fact emerges between the US and SA as well as US and UK market returns because the co-skewness changed from negative values in the pre-crisis regime to positive values in the crisis regime which also suggests that investors are expressing greater preference towards risk aversion. Another interesting fact from the market co-movements during turbulence period is the significant relationship between SHANGHAI and NSE markets while JSE and NIKKEI maintain independence with SHANGHAI both during calm and turbulent regimes. Yang et al., (2017) found in a sample of four Asian countries (China, Japan, Korea and Taiwan) that the Chinese stock market is an isolated or segmented market and regardless of the starting point of the crisis, Korea and Taiwan show greater vulnerability to external shocks compared to China and Japan.

We can infer that investors are becoming too sensitive to risk and their attitude towards risk can best be described as risk averse investors. That is, investors in the turbulent regime are more risk averse than during the calm regime and that volatile market environment imposes more discipline on the behavior of the investors in terms of portfolio selection and optimization. However, the fact that there is negative co-skewness for all markets from low to high volatility regimes, except for NSE and JSE markets, indicate that investors are riskier during the crisis period. Thus, it simply reflects the fact that investors are less risk averse in the NG and SA markets relative to investors in the other three markets. In this regard, Schwendener (2010) posits that most financial time series exhibit negative skewness, thus increasing the probability of big negative realizations and, therefore, fortifying the fat tail on the left (negative) side.

In terms of moments, we can see that the mean return ($\mu_{i=1}$) is much lower (indeed, all negative) across all the markets in the crisis period than it is in the pre-crisis period. The mean values become negative indicating a significant reduction in the size of the markets during crisis. Additionally, we see that the variances of the return ($\Sigma_{ii,1}$) become larger than it is the first (calm) regime. Furthermore, skewness

parameters ($\psi_{ii,1}$) fall across the five markets but remain the same across the regimes. Furthermore, the phenomenon of lower mean and larger variance are typical dynamics of a turbulence market behavior.

4.3 Tests for Spillover in Calm and Turbulent Regimes

Evidence in the literature suggests that as markets move from bear to bull market, the tendency for spillover albeit contagion effect heightens. The preceding analyses confirm this fact, as greater co-movements and contagion effects were found within market clusters; that is, Asian and African markets, and with the US Dow Jones market. Therefore, to test the phenomenon of volatility spillover across the markets in line with our specification in equations 3.21 – 3.24, we compute spillovers at two levels. At the first level, we present results of spillover during turbulent regime in Table 5 reveal presence of contagion effect during the turbulent period. The test statistic computed reveals perfect correlations for NG, SA, JP, CH and UK markets with the US market.

Table 5: Empirical Results of the Spillover Test in the Turbulent Regime

Test	DR	NG	SA	JP	CH	UK	US	$\forall i$
<i>Contagion Test ($i \neq j$)</i>								
<i>Correlation</i>	ρ	1.00	1.00	1.00	1.00	1.00		1.00
<i>Coskewness</i>	<i>BF</i>	2.12	1.56	12.31	5.96	2.41		-25.41

Notes: The sample period is from January 2008 to March 2018 and evidence of spillover is indicated by bold font. The hypothesis is evaluated by Dickey Ratio (DR) and BF indicates a decision reached based on Bayes Factor.

Further, there is strong co-skewness between the Japanese market and the US's as implied by the value of the Bayes factor ($\ln(BF)$) of -12.31. That is, investors trading in NIKKEI are receptive, as far as risk mitigation is concerned, to the US stocks during market turbulence than their home market.

Table 6: Empirical Results of the Structural Break Test in the Turbulent Regime

Test	DR	NG	SA	JP	CH	UK	US	$\forall i$
<i>Structural break Test (i)</i>								
<i>Mean</i>	ρ	0.30	0.57	0.10	0.82	0.60	0.98	1.00
<i>Variance</i>	ρ	1.00	1.00	1.00	1.00	1.00	1.00	1.00
<i>Skewness</i>	<i>BF</i>	0.56	0.03	-0.10	0.32	0.87	-15.21	-27.10

Notes: The sample period is from January 2008 to March 2018 and evidence of spillover is indicated by bold font. The hypothesis is evaluated by Dickey Ratio (DR) and BF indicates a decision reached based on Bayes Factor.

On structural break test, results in Table 6 show that except for the US, none of the markets has statistically significant break in mean according to the test statistic. In addition, the US remains the only country with decisive support for structural break in the skewness parameter with the value of the natural log of the Bayes factor ($\ln(BF)$) of -15.21. The probabilities for structural break in mean for NG and SA are 30% and 57%, respectively. This is suggestive to say that JSE is likely to react in turbulence than NSE. Also, the probabilities for structural break in mean for JP and CH are computed to be 10% and 82%, respectively. There is more stability in the Japanese market than in the Chinese market during turbulence regime.

4.4 Analysis of Volatility Spillover and Interdependencies

In this section, we present the analysis of volatility spillover using the class of multivariate generalized autoregressive conditional heteroskedasticity model (MGARCH). Specifically, we fit the data using Baba, Engle, Kraft and Krooner (BEKK) model and the Tse-Tsui Dynamic Conditional Correlation (DCC) model. In addition, we allow asymmetries in the conditional variances of the model so that we have two versions of the BEKK models, namely the BEKK-AMGARCH and the BEKK-MGARCH. For the DCC model, we allow the conditional variance distribution to be able to accommodate fat-tails information. Thus, we estimate two versions of the DCC models, the DCC-Normal and the DCC-student's t . Estimates from these models are reported on Table A.2 in Appendix IV.

We find evidence that conditional variances are directly affected by their past news and volatility only with respect to $\alpha_{11}, \alpha_{31},$ and α_{33} in the BEKK-AMGARCH specification. On the effects of past conditional variances on conditional variances, β_{22} and β_{33} are significant while only γ_{11} and γ_{33} are significant for the BEKK-AMGARCH specification. The log-likelihood value for the BEKK-AMGARCH specification is higher (-1054.) than that of BEKK-MGARCH model (-12234.981). Additionally, we also find that not only are conditional variances directly affected by own-volatility and news in most cases, but also by bi-directional transmission of volatility and shock (except for α_{21}). For the β coefficients (which measure the effects of past conditional variances on conditional variances) only β_{31} and β_{23} are significant. For the calm and turbulent dummies, most of the included dummies (August 2008 to September 2009) are significant. Thus, based on the results from the MGARCH models, there is significant cross-volatility spillover and own-volatility spillover across the sampled markets with time-varying correlations. In addition, we reveal, from the estimates of BEKK-AMGARCH that the contagion distribution is asymmetric and this improves the forecast of volatility and correlations among the market returns.

Setting the subscripts as $i = 1, 2,$ and 3 reflect the two emerging markets (Nigeria and South Africa markets) and one developed market (US market). We can see that there is statistically significant evidence of past shock from the US market to the Nigerian and Johannesburg markets as the parameters of cross-volatility transmission are statistically significant, that is, (α_{13} for Nigeria and α_{23} for South Africa. This confirms the expectation that contagion is transmitted from the stronger markets to the weaker markets (Hui and Chan, 2014) and Bala and Takimoto (2017). On the other hand, the coefficients of volatility transmission from the Nigerian and the Johannesburg markets, that is, α_{31} for Nigeria and α_{32} for South Africa to the US market, show that although the parameters are significant, the size of the shock transmission is relatively weak. This suggests that the pattern of bi-directional spillover transmission between the developed market (US market) and emerging markets (Nigeria and South African markets) is asymmetrical. de Oliveira et al., (2018) report similar findings in the case of Brazilian market with the United States'.

Furthermore, results presented in Appendix V, Table A.3 report the tri-variate DCC-MGARCH model under two distributional assumptions--the Gaussian normal distribution and the Student's t . The ψ 's correspond to the mean parameters while the β 's correspond to the GARCH parameters. The parameters governing the DCC recursion in Table A.3 are DCC (α) and DCC (β). The v statistic and improvement in the log-likelihood achieved by the DCC-MGARCH with t density shows evidence against the Gaussian DCC-MGARCH model. Also, the parameters governing the dynamics of correlations are significant for all models and the persistence parameters for the volatilities are all greater than 0.9 with the stationarity conditions satisfied. The DCC (α) and DCC (β) are all highly significant. For the DCC (α) the estimate decrease with the introduction of a more flexible density in all models, while the estimates of DCC (β) increase in all cases. In addition, $\alpha + \beta$ is 0.596, in the DCC Gaussian, while it is 1.069, slightly greater than unity in the DCC-Std. - t distribution.

Specifically, the result shows that the DCC parameters for the US markets relating to the time-varying variances and correlations for the Nigerian and South African markets are able to describe the presence of fat-tailed behavior and co-skewness in their distribution. Equally, the mean distributions are negatively skewed for both markets (Nigeria and South Africa), except that of the US. Negative skewness implies that negative returns are more common than positive returns. Thus, the emerging markets (Nigerian and South Africa) are said to have relatively more stable return distributions than the developed market (US market).

5. CONCLUDING REMARKS

The presence of fat tails phenomenon in financial market accommodates the likelihood of large positive and negative shocks. The naivety in assuming normal distribution in market returns tends to underestimate the variance in times of crises and overestimates it in low volatility times. This might exert serious consequences on asset allocation and risk management. Regime-switching models that allow parameters to switch over time lead to a better fit in modelling volatility of financial markets.

This paper analyzed patterns of co-movements, contagion effects, dependence and independence among the stock markets in six (6) countries namely Japan (JP), China (CH), Nigeria (NG), United Kingdom (UK), United States (US) and South Africa (SA) using the Markov Regime-Switching Model with skew normal distribution and the Markov Chain Monte Carlo (MCMC). In addition, the asymmetric multivariate GARCH (AMGARCH) model with BEKK and DCC specifications were applied to detect the presence or otherwise of spillover and contagion effects from and across the financial markets, respectively. The paper utilized data spanning the period, January 2000 to December 2018. Preliminary investigations reveal evidence of nonlinearities, fat tails, and high incidence of correlations among stock returns in the six markets across calm (bear market) and turbulent (bull market) regimes. The paper intuitively identified calm and turbulent regimes based on a historical event and the strategic role of the US market as the originator of crisis in the sample. The results showed that the behavior of market returns differs across the two regimes--calm and turbulent. Market co-movements with the Dow Jones rises during turbulence period than during tranquility, particularly for the NSE and JSE.

Furthermore, while Nigeria's NSE and the JSE are knotted together, the Japanese NIKKIE and the Chinese SHANGHAI show evidence of strong independence. We report evidence of bi-directional spillover transmission between the developed market (US market) and emerging market (Nigeria and South African markets) to be asymmetrical and the tendency for the markets to drift to higher spillovers from calm to turbulent regimes. This, invariably, validates the expectation that contagion is transmitted from the stronger markets to the weaker markets.

It is worthy of note that understanding the patterns of volatility transmission and interrelationship existing among financial markets will help investors make the right investment decisions regarding portfolio optimization and financial risk management. Policymakers and regulators as well can use this knowledge in planning and implementing appropriate regulatory framework. This is most useful to Nigeria in view of its financial interconnectedness with the United States, Asian countries, most especially China, and new development under the African union that now brings South Africa more closely to Nigeria.

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APPENDIX I

Figure A.1: Plot of Fat-Tails in the Calm Regime – UK, US & JP

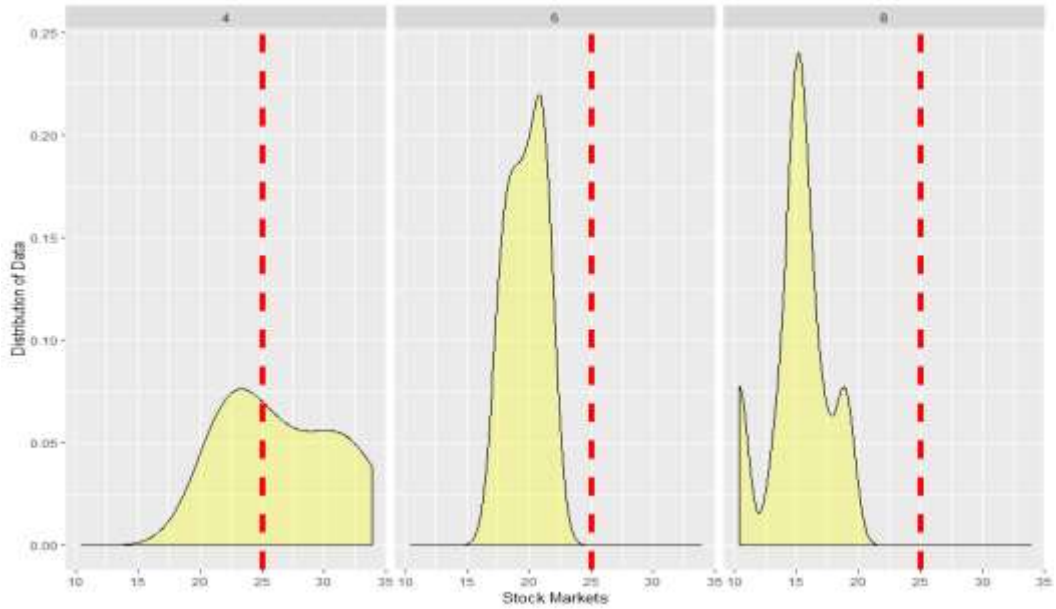


Figure A.2: Plot of Fat-Tails in the Turbulent Regime – UK, US & JP

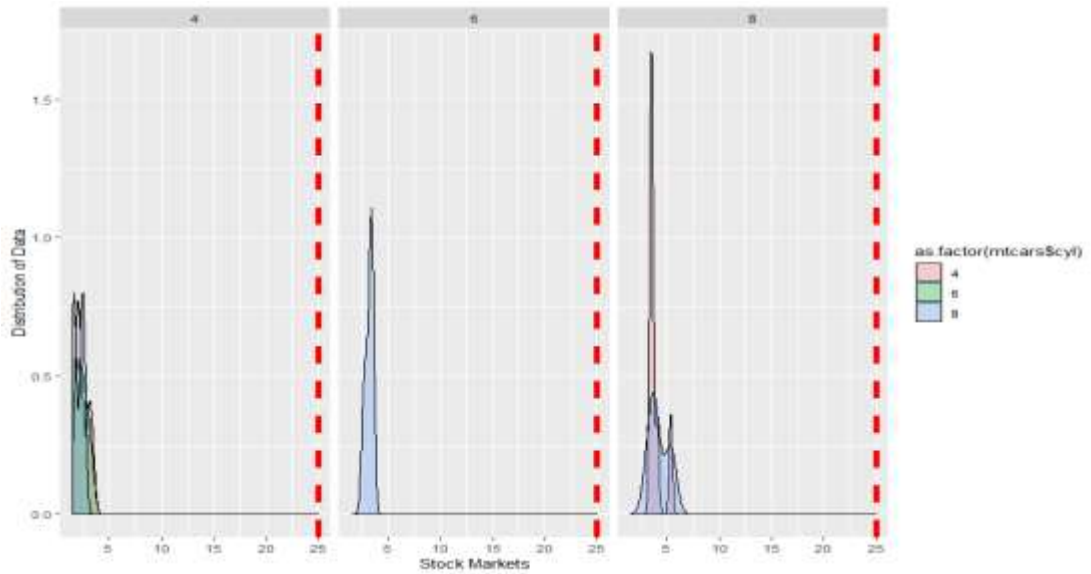


Figure A.3: Plot of Fat-Tails in the Calm Regime – CH, SA & NG

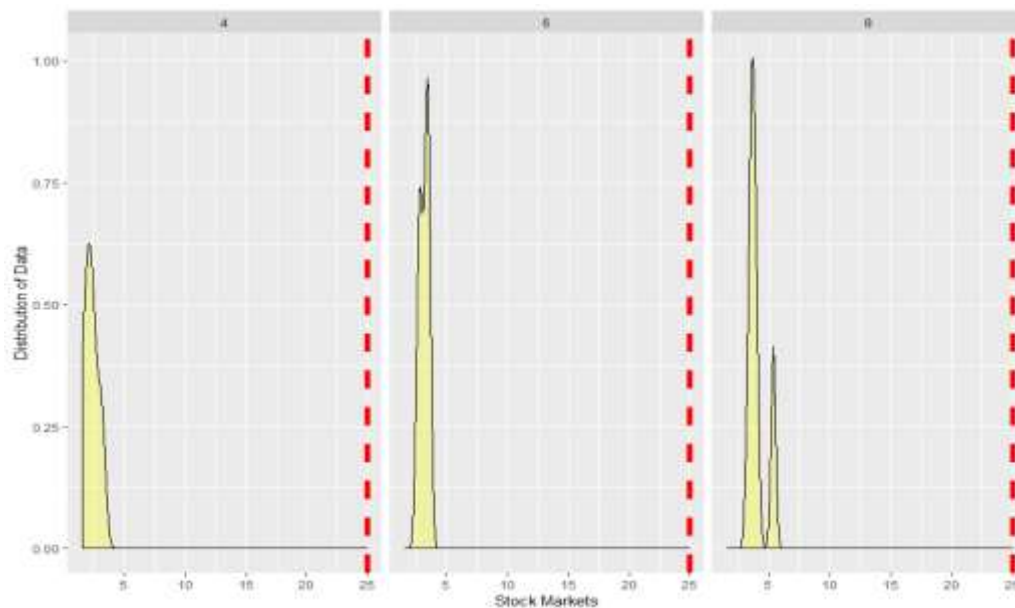
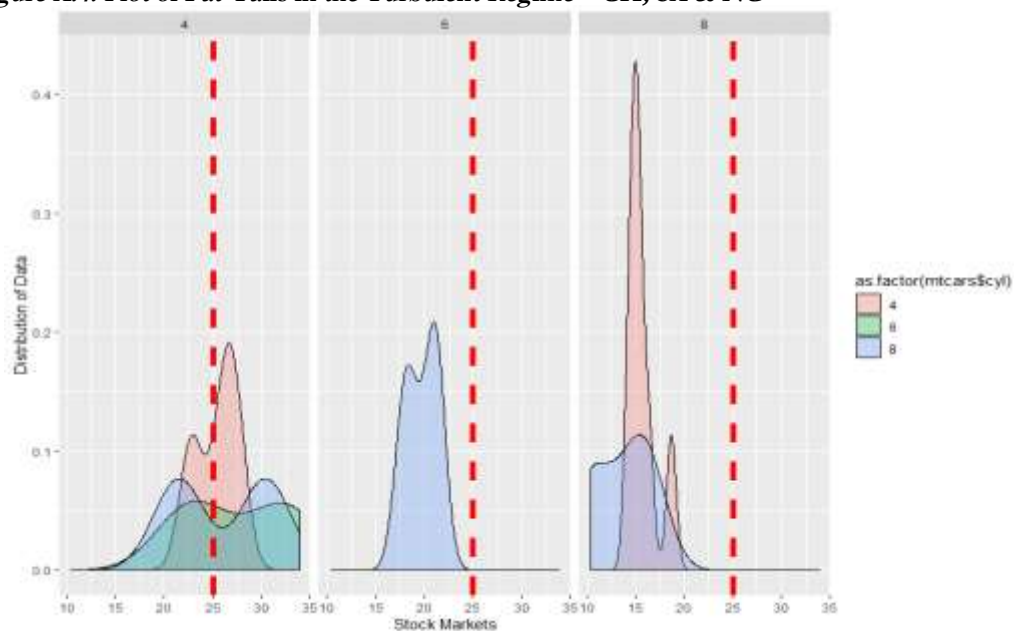


Figure A.4: Plot of Fat-Tails in the Turbulent Regime – CH, SA & NG



APPENDIX II

Table A.1 Ipek's Test of Normality in the Calm Period

<i>Test</i>	<i>Calm Regime</i>			<i>Turbulent Regime</i>		
	T-statistic	p-value	1: Normal, 0: Non-normal	T-statistic	p-value	1: Normal, 0: Non-normal
<i>KS Limiting form</i>	5.7188	0.0031	0.0000	5.7188	0.0097	0.0000
<i>KS Stephens Modification</i>	4.7478	0.0930	0.0000	3.7478	0.0042	0.0000
<i>KS Marsaglia</i>	3.7188	0.0500	0.0000	6.7188	0.0229	0.0000
<i>KS Lilliefors Modification</i>	5.7607	0.0076	0.0000	6.1479	0.0010	0.0000
<i>Anderson-Darling Test</i>	0.5951	0.1204	0.0000	3.5951	0.1004	0.0000
<i>Cramer-Von Mises Test</i>	7.0956	0.0295	0.0000	7.0956	0.0295	0.0000
<i>Shapiro-Wilk Test</i>	5.9186	0.0930	0.0000	4.9186	0.0930	0.0000
<i>Shapiro-Francia Test</i>	69.206	0.0935	0.0000	3.9206	0.0935	0.0000
<i>Jacque-Bera Test</i>	2.9892	0.0043	0.0000	2.9892	0.0243	0.0000
<i>D'Agostino & Pearson Test</i>	0.6285	0.2988	1.0000	4.6285	0.0988	0.0000

Source: Researchers' computations

APPENDIX III

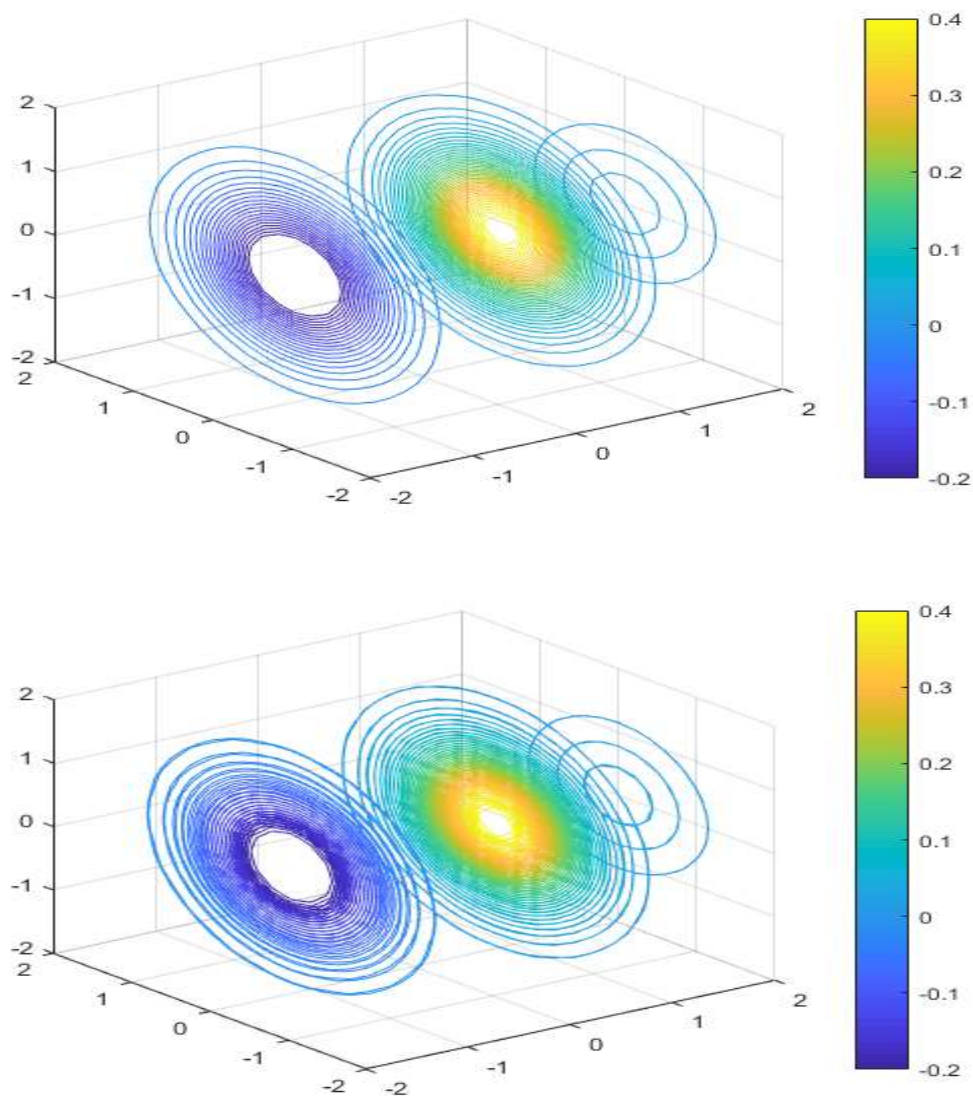


Figure A5: Contour plots of the bivariate skew-normal density

APPENDIX IV

Table A.2: Estimates of BEKK-AMGARCH and BEKK-MGARCH

Parameter	BEKK-AMGARCH	BEKK-MGARCH
δ_1	0.4567** (0.0012)	0.4321** (0.0413)
γ_1	0.2134** (0.0213)	0.3451** (0.0129)
δ_2	0.9823* (0.0912)	0.2198** (0.0387)
γ_2	0.8765** (0.0489)	0.8765 (0.3421)
δ_3	0.0981* (0.0891)	0.7654 (0.1233)
γ_3	0.2387** (0.0036)	0.0765 (0.2365)
s_{11}	0.1561** (0.0017)	0.0921** (0.0113)
s_{21}	0.2651** (0.0113)	0.9051** (0.0276)
s_{22}	0.8723* (0.0812)	0.8765** (0.0198)
s_{31}	0.6565* (0.0989)	0.5987 (0.7651)
s_{32}	0.0981* (0.2351)	0.6514 (0.1093)
s_{33}	0.9887** (0.0016)	0.9812 (0.2987)
α_{11}	0.4567** (0.0012)	0.4321** (0.0413)
α_{12}	0.2134** (0.0213)	0.3451** (0.0129)
α_{13}	0.9823* (0.0912)	0.2198** (0.0387)
α_{21}	0.8765** (0.0489)	0.8765 (0.3421)
α_{22}	0.0981* (0.0891)	0.7654 (0.1233)
α_{23}	0.2387** (0.0036)	0.0765 (0.2365)
α_{31}	0.5665** (0.0329)	0.6543 (0.9876)
α_{32}	0.0761* (0.0761)	0.3211 (0.6543)
α_{33}	0.6547** (0.0006)	0.2134 (0.1431)
β_{11}	0.9877**	0.5431**

	(0.0082)	(0.0313)
β_{12}	0.2874**	0.3451**
	(0.0183)	(0.0129)
β_{13}	0.7653*	0.2198**
	(0.0892)	(0.0387)
β_{21}	0.6545**	0.8765
	(0.0129)	(0.3421)
β_{22}	0.0651*	0.7654
	(0.0641)	(0.1233)
β_{23}	0.9877**	0.0765
	(0.0016)	(0.2365)
β_{31}	0.9865**	0.6543
	(0.0419)	(0.9876)
β_{32}	0.0891*	0.3211
	(0.0651)	(0.6543)
β_{33}	0.2317**	0.2134
	(0.0019)	(0.1431)
γ_{11}	0.0222**	- (0.0001)
γ_{12}	0.5434**	- (0.0093)
γ_{13}	0.8523*	- (0.0202)
γ_{21}	0.2167**	- (0.0021)
γ_{22}	0.0987**	- (0.0023)
γ_{23}	0.2340**	- (0.0026)
γ_{31}	0.1235**	- (0.0021)
γ_{32}	0.0891*	- (0.0711)
γ_{33}	0.1231**	- (0.0011)
v	0.4567**	0.4321**
Log-Likelihood	-1054.123	-12234.981
AIC	23.46	31.56
SBC	12.45	14.71

Note: [] indicates standard errors and ** and * indicate significance at 5% (or better) and 10%, respectively.

APPENDIX V

Table A.3: Estimates of DCC-Normal and DCC-Std. t

<i>Parameter</i>	<i>DCC-Normal</i>	<i>DCC-std.'s -t</i>
ψ_{11}	0.1547** (0.0011)	0.4321** (0.041)
ψ_{12}	0.2294** (0.0313)	0.3451** (0.0129)
ψ_{21}	0.1843*	
0.2198**	(0.0811)	(0.0387)
ψ_{31}	0.1165** (0.0189)	0.8765 (0.3421)
β_{11}	0.1277** (0.0021)	0.5431** (0.0313)
β_{12}	0.1874**	
0.3451**	(0.0183)	(0.0129)
β_{13}	0.7223** (0.0082)	0.2198** (0.0387)
β_{21}	0.1545** (0.0229)	0.8765 (0.3421)
β_{22}	0.0251* (0.0241)	0.7654 (0.1233)
β_{23}	0.2277** (0.0216)	0.0765 (0.2365)
β_{31}	0.1165** (0.0019)	0.6543 (0.9876)
β_{32}	0.2391* (0.0751)	0.3211 (0.6543)
β_{33}	0.1117** (0.0019)	0.2134 (0.1431)
$DCC(\alpha)$	0.5622** (0.0001)	0.8523** (0.0093)
$DCC(\beta)$	0.0334**	
0.2167**	(0.0023)	(0.0202)
v	0.4567**	
0.4321**	(0.0023)	(0.0002)
Log-Likelihood	-1054.123	-
12234.981		
AIC	23.46	31.56
SBC	12.45	14.71
LR(Skew)	34.9567*	

Note: [] indicates standard errors and ** and * indicate significance at 5% (or better) and 10%, respectively.