Regime Switching in Sub-Saharan Frontier Equity Markets - A Case Study of the Ghana Stock Exchange Index

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Abstract
We investigated regime switching behaviour of the broad aggregate returns of the Ghana Stock Exchange within the context of frontier markets. The data covered the daily period from January 04, 2011 to March 31, 2017. We made the following findings: (a) there are clear market regimes corresponding to periods of tranquillity and turbulence as demonstrated by the vastly different unconditional volatilities associated with the low and high regimes in the data (b) contrary to investor beliefs, frontier markets are less risky than reported in the popular press and (c) the returns from frontier markets are positively skewed. The regime switching model employed was compared to the workhorse GARCH(1,1) model used for volatility estimation in finance using the Deviance Information Criteria. In our findings, the MS-GARCH performed better than the GARCH(1,1), confirming recent studies in volatility modeling. The implications of these findings for trading strategies, investment and portfolio choices and risk management have been highlighted. For policymakers this study will provide a counter argument for granting tax exemptions to global investors on the basis of perceived elevated risk in frontier markets.

Keywords: Regime-switching, frontier markets, Markov Switching-GARCH, transition matrix, global investors

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Introduction
Volatility is a very important measure in financial markets. It is ever present in investment and portfolio management, pricing of financial instruments, trading and financial risk management. Investors have

long known that different market conditions affect the returns on investments in financial markets. Trading strategies perform differently under different market conditions. In highly volatile markets where asset prices are falling, for example, investors tend to adopt bearish strategies like shorting assets to profit from falling asset prices and hedging their trades using derivative instruments. Knowing when to adopt a particular strategy is seen as a competitive strategy in today's markets.

Nowhere are these market conditions more pronounced than in a country's equity market that is highly influenced by the underlying macroeconomic, political and social developments. The business cycles of a country are closely mirrored in the behaviour of the financial markets. Investors face a lot of uncertainty when they trade in the financial markets across all assets classes. These uncertainties can be the result of the state of the economy, corporate announcements, political upheavals or investor psychology with respect to the processing of news. Danielsson (2002) made the remarkable observation that "market data is endogenous to market behavior. . ." (pg. 1). And market behaviour in turn is informed by risk drivers in the underlying economy. Thus, any attempts at modelling volatility must of necessity take account of these developments in a given economy.

Conditional volatility varies across time but it is essentially state dependent. During periods of economic expansions, firms and businesses are buoyed by the general rise in productivity which boosts further investment in production capacity. This boosts activity in their stocks and dampens the volatility associated with trading in their equities. On the contrary, recessions dampen business activity typically with low employment of productive resources (Roberts & Tybout, 1997). Demand for firm products tend to be generally low. Debt to equity mix of the capital structure of firms becomes high as a result of low profitability in a slowing economy (Tang & Yan, 2010). In this state, firms become highly leveraged and this spooks investors into selling their holdings thereby increasing market volatility. Exogenous shocks characterised by a departure from a low to a higher regime reflects investor nervousness in the stock markets. Macroeconomic volatility, geopolitical events, local conflicts, foreign exchange crisis, fall in world commodity prices and pending national elections are frequent events that spook investors to rethink their strategies particularly in frontier equity markets (Aggarwal, Inclan, & Leal, 1999).

Globally, the financial crisis of 2008 is an example of an event that led to extreme volatility in markets across all assets. The massive sell off it unleashed subsequently led to extreme volatile trading sessions in the developed and some emerging markets across the globe. It was not until central banks of the developed world intervened through a combination of ultra-low interest rates and other unconventional monetary policies were the markets restored to normalcy. In the light of these events in the developed and much of the emerging markets, investors are allocating substantial investment funds to hitherto unknown markets (Chan-Lau, 2012). As investors pour into frontier markets assets, however, there is still a perception of above average risks in these markets. The motivation for this article, therefore, is to provide a characterisation of risk using Markov regime switching in sub-Saharan African frontier markets using the Ghana Stock Exchange as typical of such markets. A clearer and somewhat better appreciation of the evolution of time-varying volatility is achieved by looking at volatility within regimes which are associated with the state of the economy instead of assuming a single regime in the data. We thus investigate in this paper the existence of regimes in the Ghanaian equity markets using the Markov regime switching and show how the model tracks the time-varying volatility regime-by-regime as opposed to conventional GARCH(1,1) models which assume a uniform time dependent heteroscedastic evolution.

The paper uses the daily returns of the Ghana Stock Exchange Index (GSEI) spanning January 04, 2011 to March 31, 2017 for the analysis. Fragile institutions and systems and lack of long term policy planning in typical frontier economies mean policy can change suddenly. So we model the change as an unobserved stochastic process using Markov regime switching. We found that the Markov regime switching model characterise volatility of frontier markets and outperformed the conventional GARCH(1,1), a generally accepted workhorse of volatility models in finance (Engle, 1982). We reached this conclusion through a comparison of their Deviance Information Criteria (DIC), a more conservative model selection criterion. Another important finding is the positive leptokurtic returns of the aggregate market in frontier markets. This contrasts findings in the developed markets where aggregate market returns tend to be negatively skewed. Finally, our research reveals that equities in frontier markets are less volatile than previously thought. This finding should spur further investments in equities of the frontier markets.

The paper is novel in many ways. It is the first, to be best of our knowledge of the literature, to estimate the volatility of returns in sub-Saharan African frontier market using a regime switching model. There are lots of papers on regime switching involving different asset classes. However, all these are centred on developed and emerging markets. Again this paper unlike similar ones in this track of volatility research in emerging and frontier markets, for example Haque et al. (2004) and Gomes and Chaibi (2014) with the latter focusing specifically in equity markets in the MSCI Frontier Index, accounts for the effects of asynchronous and thin trading on market returns. Our work also fills an important knowledge gap in the frontier equity markets literature in taking into consideration the various states of the economy in modeling the volatility of stock market returns using the Ghanaian equity market as representative of frontier economies. Global investors are wary of investing in frontier equity because of the perceived risks that lurk in these markets. This is due in part to lack of research and understanding of these markets. With this research, investors are better positioned to make the right trading and investment decisions based on an understanding of the risk dynamics in the frontier markets. The findings are generic enough to be applicable to frontier equity markets within Sub-Saharan Africa (SSA). Finally, the paper showed that Markov switching is the appropriate model for modeling and forecasting volatility on frontier equity markets. It achieves this by incorporating the nonlinear characteristics of the returns in the analysis using a two-stage analysis of maximum likelihood and Markov Chain Monte Carlo estimation to get around the problems of path-dependency of regime switching models.

The rest of the paper is organised as folows. Section two is a review of the literature consisting of the developments in the use of regime switching in the equities, foreign exchange and commodities markets in the developed and emerging markets. Here we provide a formal definition of "frontier markets", discuss their characteristics and role in global investment portfolios, survey the risks of investing and how to properly characterise the volatility associated with market returns in frontier markets. Section three looks at the Markov regime switching model specification. The analysis and results of the market data takes place in section four. Section five looks at the implications for investors and policymakers. Finally, section six concludes with implications for investments and policymakers.

Literature Review

Frontier Markets: Definition, Characteristics and Investment Opportunities

Girard and Sinha (2008) identified frontier markets as a group of less known, less accessible, small, and illiquid markets which are less researched. Indeed the practitioner literature is replete with studies on investment strategies in the frontier markets compared to the academic literature. The term "frontier markets" was originally coined in 1992 by the International Finance Corporation (IFC), a private financing arm of the World Bank and a leading investor in frontier market assets. It is a term the IFC used to describe markets consisting of a subset of very small emerging markets with lower market capitalization, less open and less liquidity compared to the more developed and emerging markets. Speidell and Krohne (2007) reflects on the fact that many investors perceive frontier markets "as being in decline, ravaged by wars, disease, famine, and authoritarian governments. . . " (p. 1), a view they attribute to media reports rather than reality. Being less known to investors, frontier markets are laden with opportunities of making decent returns on investments because they are less crowded. Again, frontier markets are almost synonymous with countries with attractive economic fundamentals, lower volatility contrary to what is perceived, attractive valuation of investable assets, opportunities for diversification as a result of low correlations with developed and emerging market assets and favourable demographics. Indeed frontier markets have found themselves in global indices used by the investing community. Notable among them are the S&P Frontier BMI Index, MSCI Frontier Market Index, Russell Frontier Index and the FTSE Frontier Market Index among others (Sukumaran, Gupta, & Jithendranathan, 2015).

Frontier markets as an asset class has been noted to providing an important diversification as a result of their low correlation with the returns of markets of the emerging and developed countries (Berger, Pukthuanthong, & Yang, 2011). Returns from much of the developed countries have sagged for more than a decade now. Yields have dropped precipitously following the coordinated ultra-low and sometimes negative interest rate regimes instituted by the monetary authorities in the developed countries. However, frontier markets are perceived to be fraught with risks that can surprise investors quickly. Markets are prone to sudden market sell-offs, tightening of regulations for expatriation of profits by foreign firms, political upheaval and currency crises (Hassan, Maroney, El-Sady, & Telfah, 2003). These cycles of volatility regimes are best captured with a regime switching volatility model.

Frontier Market Risks

Sources of risks in equity markets in frontier markets have been highlighted extensively in the practitioner literature. Foremost on the minds of investors is political instability, civil unrest and their disruptive effects on the markets. Conflicts affect every facet of the economy. The narrative on most SSA countries is that of military take-overs, civil strife and outright civil wars. Countries from Mali through Cote d'Ivoire, Nigeria to Zimbabwe have experienced some form of civil disruption or social unrest over the last decade. Zimbabwe had the largest and most thriving stock market in SSA excluding South Africa. Inconsistent government policies including massive currency devaluations triggered by the land reforms scared away investors from the Harare Stock Exchange leading to considerable reduction in total market capitalisation of the stock market. Recent events in Cote d'Ivoire provides important lessons on the devastating effects on a country's financial markets during conflicts. This has been documented extensively in Klapper, Richmond and Tran (2013) and Salami (2016).

Low market liquidity has been identified as an obstacle to the smooth functioning of frontier equity markets. Gueye et al. (2014) identified lack of liquidity as the main reason why investors demand high returns in frontier markets in Sub-Saharan Africa. Lack of liquidity is reflected in thin trading and high transaction costs. Illiquidity continues to be a problem as noted in Hoekman, Senbet and Simbanegavi (2017). Liquidity affects the ability to undertake large trades. Low trading volumes are cost inefficient. Funds buying or selling large orders have problems in trade execution. In the end they pay more to buy or receive less to sell. This affects their returns on investment. It also affects the expansion of these markets and types of financial instruments that can be found in them. Loukil et al. (2010) found evidence that this impacts investor returns in the Tunisian equity market. Generally, listed companies are very small compared with emerging markets and total market capitalisation compared with the gross domestic product of the countries is very low.

Of greater concern to global investors is the regulatory framework in the frontier markets. Changing or uncertain regulatory framework constrains investment decision-making. A lack of strong institutions in frontier markets means unanticipated changes in regulations guiding margin trading, transaction fees, commissions on trades, capital control and taxes. These rules change arbitrarily with personalities at the helm of affairs of the market regulatory institutions. As a result, investors for the most part adopt a wait-and-see attitude whenever there is an impending election or proposed change of personalities in charge of market related regulatory institutions. Following an earlier work by Dupasquier and Osakwe (2006) and Dahou, Omar and Pfister (2009), Anyawu (2012) found that regulatory uncertainty is one of the risks cited by global investors coming to Africa. Isimbabi (1997) writing two decades ago summarised the situation, thus ". . . the destabilizing effects of introducing stock markets into economies with underdeveloped legal, regulatory, and monetary systems can produce economic instability that outweighs potential gains" (p. 142).

Measuring Frontier Market Volatility

Equities exhibit regime-switching behaviour in all markets across different asset classes. This corresponds to times of high and low volatility usually associated with bear and bull market periods respectively. In some asset markets, this change can represent blips in trading especially when markets are choppy. In others, still, the change can be temporary extending to several trading weeks or months while in most severe cases it can be a permanent structural shift in the dynamics of the markets.

Numerous time series approaches have been proposed in the financial econometrics literature to model this behaviour. In particular, the work on Markov regime switching behaviour was laid in the seminal works of Hamilton (1989; 1990) and later developed into Markov-switching GARCH (MS-GARCH) by (Hamilton & Susmel, 1994) in the context of equity markets. Subsequent to that, regime switching literature in finance and economics has exploded over the years. Researchers have used this concept in all areas in finance. Markov regime switching models are a generalisation of the generalised autoregressive conditional heteroskedastic (GARCH) model of Bollerslev (1986). They are an extension of the GARCH to the nonlinear paradigm, able to capture the properties of volatility within each regime found in the data by allowing the GARCH parameters or coefficients to vary flexibly across each state of the world. In a way, MS-GARCH models are like piecewise polynomial nonlinear GARCH models approximating the state of each regime.

Hamilton and Lin (1996) presented evidence of volatility varying with the business cycle. Numerous studies, for example, Bauwens et al. (2014) and Lamoureux and Lastrapes (1990) reported that volatility predictions made by classical GARCH-type models fail to capture the true variations in volatility in nonlinear time series with regime changes. Many researchers, thus, discussed the importance of taking into account the regime changes in modelling and improving forecasts of volatility in financial time series (Ephraim & Merhav, 2002; Franke, 2012; Tong, 2015; Tyssedal & Tjostheim, 1988).

Engle and Patton (2001) underscored the ability to capture pronounced persistence, mean-reversion and asymmetry as the desirable properties a good volatility model needs to possess. However, they did not consider regime changes in the data which will likely affect the performance of the GARCH model. Haas, Mittnik and Paolella (2004a) recommended that volatility estimation and prediction should be based on models that incorporate regime switching in the data. Turner, Startz and Nelson (1989) demonstrated the superiority of regime switching over traditional GARCH-type models in analyzing stock markets data. Indeed for a long time, research in financial econometrics has focused on improving the predictive ability of GARCH models. Klaassen (2002) is of the view that the predictions of GARCH models can be improved by the adoption of regime switching models which allow the parameters of the GARCH to vary over time in the data. This approach, according to Ardia et al. (2017) allows for volatility predictions that can be quickly responsive to the levels of unconditional volatility. Calvert and Fisher (2004) showed that GARCH models are a smooth transition processes and are thus unable to capture sudden switches that characterise financial time series. Indeed these switches arising out of the uncertainties of the economy define the trading activities of equities in frontier markets. Majority of equities in frontier markets trade asynchronously usually in response to some sporadic developments in the economy.

Diebold (1986) also noted the lack of fit of GARCH models to interest rate data and attributed it to changing monetary policies which influence the statistics generated by the data. By adopting a regime switching model rather than straight GARCH, we build a parsimonious specification model with fewer lags to characterise the data generation process of the underlying mechanism. Finally, using S&P 500 returns with weekly, daily, 10-minute and 1-minute frequencies, BenSaida (2015) showed that regime switching models are far more efficient in detecting different regimes in the data.

Methodology

The notation used in the model is due to Haas et al. (2004b) and expanded on by Bauwens et al. (2010). Consider a stationary time series $\{y_t\}^{T}_{t=1}$ demeaned and partition into k non-overlapping regimes i.e. $R_1 \cup R_2 \cup \ldots \cup R_k = R$ and $R_i \cap R_j = \emptyset$ where $i \neq j$ and $R_i s$ are the regimes. The regime indicator $k \in \{1,2,3,\ldots,K\}$ is an unobserved Markov process. The data generating process under MS-GARCH is specified as:

$$y_t = \mu_t + \sigma_t u_t,\ u_t \sim iid\,(0,1) \qquad (1)$$

$$\sigma_t^2 = \omega_{S_t} + \alpha_{S_t}\,\varepsilon_{t-1}^{\ 2} + \beta_{S_t}\,\sigma_{t-1}^{\ 2} \qquad (2)$$

where the assumptions $\omega_{S_t} > 0, \alpha_{S_t} \geq 0,\ \beta_{S_t} \geq 0$ are imposed in **(1)** to ensure a positive variance and $\varepsilon_t = y_t - \mu_{S_t}$. The particular regime $s_t = \{1,2,\ldots,K\}$ is a stochastic process and data dependent. The persistence of each regime follows a first-order Markov process given by the transition probability matrix for a two regime model of the form:

$$P = \begin{bmatrix} P(S_t = 1 \mid S_{t-1} = 1) & P(S_t = 2 \mid S_{t-1} = 1) \\ P(S_t = 1 \mid S_{t-1} = 2) & P(S_t = 2 \mid S_{t-1} = 2) \end{bmatrix} = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix} \quad (3)$$

The same logic can be extended for more than two regimes. Each regime S_t generates returns y_i with a probability measure $\{\pi_i\}$. Under the first-order Markov process, state information depends on the most recent data point, all past information is given a weight of zero.

Following the work of Hamilton and Raj (2002), the probability of a change from regime i and j follow a logistic model given as:

$$P(S_{t+1} = j \mid S_t = i, z_i) = \frac{\exp(\beta y_{t-1})}{1 + \exp(\beta y_{t-1})} \quad (4)$$

for some $z_t \in Z_t$ and $0 < P_{ij} < 1$ for all i,j which belongs to the state space $\{1,...,K\}$. An additional Markov property requires that $\Sigma^{K}_{j=1} P_{ij} = 1$ for any $I \in \{1,...,K\}$. This allows the regime switching model to adjust its persistence to the state of the economy. Other approaches to modeling the transition probability have been suggested by Diebold, Lee and Weinbach (1994), Filardo (1994) and Durland and McCurdy (1994).

Estimation

We estimate the parameters $\theta = (\mu_t, u_t, \sigma_t, \omega_{S_t}, \alpha_{S_t}, \beta_{S_t})$ simultaneously in a two-stage process using maximum likelihood estimation (MLE) recommended by Augustyniak (2014) and the adaptive random-walk Metropolis sampler of Vihola (2012) using the parameters from the MLE as starting values for the sampler. The estimation of MLE for the Markov switching model is prone to convergence to local maxima because of they are path dependent; hence the use of the Bayesian approach incorporating the Markov Chain Monte Carlo (MCMC) sampling procedure (Mullen, Ardia, Gil, Windover, & Cline, 2011). For a return series consisting of a vector of $y = \{y_1, . . ., y_T\}'$. the likelihood function is:

$$L(\theta \mid y) = \Pi^{T}_{t=1} f(y_t|\theta, I_{t-1}), \quad (5)$$

where $f(y_t|\theta, I_{t-1})$ refers to the probability density function of y_t given the past information set I_{t-1} and the model parameters given by θ. To incorporate the regimes $\{1, ..., K\}$, the conditional density of y_t is modified as:

$$f(y_t|\theta, I_{t-1}) = \Sigma^{K}_{i=1} \Sigma^{K}_{j=1} P_{ij}\, z_{i,t-1} f_{\varphi}(y_t \mid s_t = j, \theta, I_{t-1}), \quad (6)$$

where $z_{i,t-1} = P(s_{t-1} = i \mid \theta, I_{t-1})$ is the filtered probability of state i at time t-1. We thus maximise the logarithm of the maximum likelihood of **(6)** to obtain the estimator Θ. These parameter estimates are used as the priors for the adaptive random-walk Metropolis-Hastings sampler (Hastings, 1970; Metropolis, Rosenbluth, Rosenbluth, Teller, & Teller, 1953) to get the final values of the estimator Θ. Inference is then based on this vector of parameters Θ.

Data and Results

The data for the analysis came from the daily GSE All-Share Index spanning the period from January 04, 2011 to March 31, 2017 giving 1549 data points. Ghana, as of August, 2017, is in the FTSE Frontier Market Index Series. We calculated the log-returns from

$$r_t = In\left(\frac{P_t}{P_{t-1}}\right)$$

where P_t is the price at time t to obtain a total of 1548 data points.

Descriptive Statistics

A plot of the index shows how the level has evolved over the sample period. The index peaked around January 2014 and remained at that level with marked fluctuations until about July 2015. The market calmed thereafter with the level fluctuating around a downward trend until January 2017 when it bottomed up.

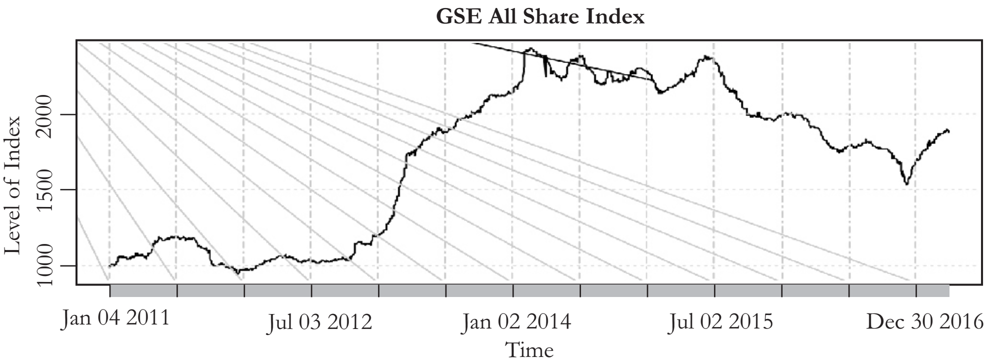

Figure 1: Plot of the GSE All Share Index

The histogram of log-returns with the normal curve superimposed on it is shown in Fig. 2. The graph shows deviations from normality. The skew is slightly positive at 0.38 with a kurtosis of 5.5 confirming the presence of fat tails in the data. This is an important difference in the market returns of the frontier markets on one hand and the developed markets on the other hand where Albuquerque (2012) found that overall aggregate market returns are left tailed whereas individual firms' returns are positively skewed. In the emerging markets, such positive skewness is well documented in Bekaert et al. (1998). Brennan (1993) reasoned that agency problems may induce such asymmetries in the data generating process for the returns.

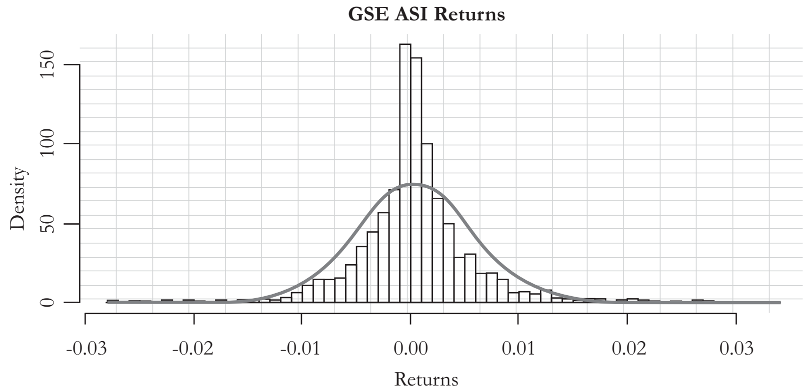

Figure 2: Histogram of the GSE All Share Index Returns

An Anderson-Darling test yielded a *p-value* < 2.2e-16 confirming the alternate hypothesis that there are observable differences between the data and the normal distribution.

We conducted the nonlinear test of Tsay (1986) to assess the nonlinearity in our data series. The test produced a test statistic of 2.107 with a *p-value* of 0.00015 for eight lags. We thus reject the null hypothesis at the 1% significant level that the series follow an autoregressive process and conclude that we have a nonlinear data series. A plot of the log-returns, the squared log-returns and absolute log-returns of the GSE All Share Index is shown in Figure 3. There are regions of extreme volatility in the returns followed by periods of relative tranquillity.

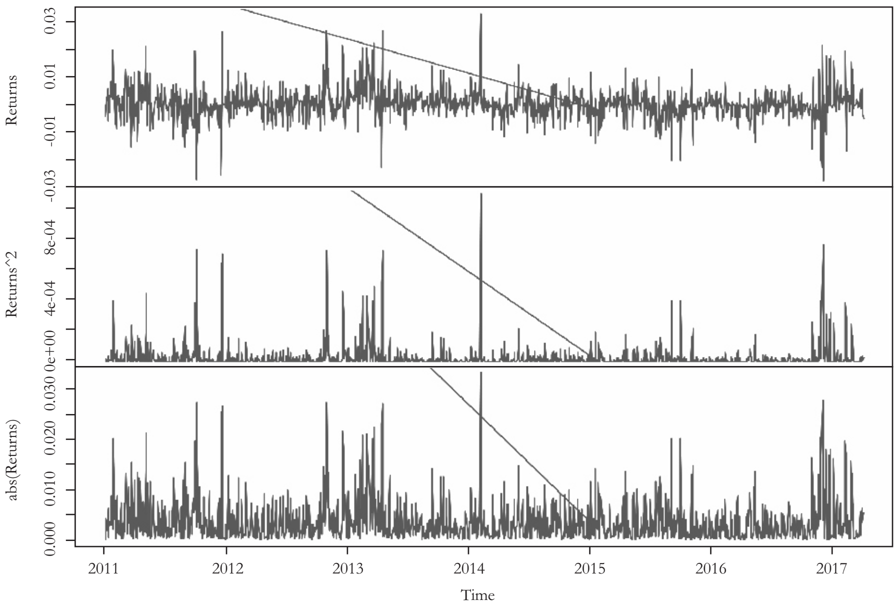

Figure 3: Graphs of the returns, the squared returns and the absolute returns of the GSE index

An augmented Dickey-Fuller test of the returns gave a p-value of 0.01 confirming the stationary of the returns.

Thin and asynchronous trading remain a problem in frontier markets as report by Appiah-Kusi & Menyah (2003) and Mlambo & Biekpe (2005) in their study of the Ghanaian and Nigerian equity markets. Scholes & Williams (1977), Dimson (1979), Fowler & Rorke (1983) and Lo and MacKinlay (1990) reported returns are likely to be biased as a result of thin trading. In regime switching work, for example, asynchronous trading through the effect of stale prices is likely to induce spurious regimes in the data. We therefore used the method recommended by Miller, Muthuswamy & Whaley (1994) and Claessens, Dasgupta & Glen (1995) to adjust the log-returns. The analysis subsequent to this is based on the adjusted returns.

A plot of the autocorrelation of the returns, the squared returns and absolute returns is shown in Figure 4. This shows significant autocorrelations going as far is the twenty-fifth lag, suggesting the presence of ARCH effects in the data.

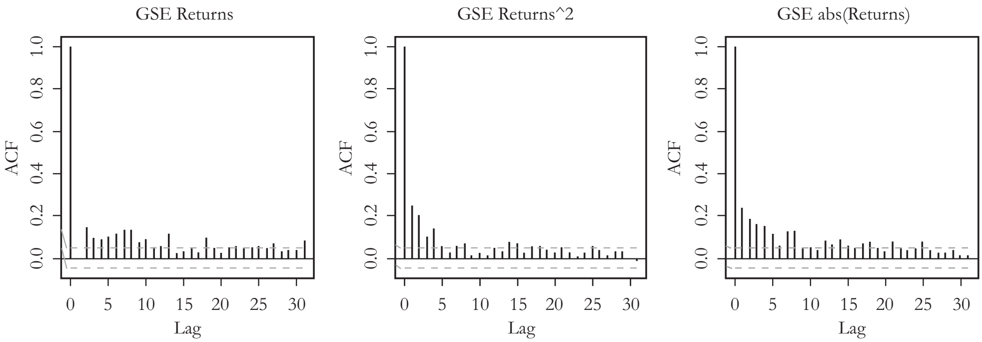

Figure 4: Autocorrelation plot of the returns, squared returns and absolute returns

The Lagrange Multiplier (LM) test of Engle (1982) for the presence of conditional heteroscedasticity or ARCH effects was conducted. The LM test with twelve lags gave a chi-square of 146.48 and a $p < 2.2 * 10^{-16}$ confirming the presence of strong ARCH effect in the data.

Regime Switching Analysis

A GJR-GARCH of Glosten, Jagannathan and Runkle (1993) with *student-t* distribution is assumed in each regime in the Markov switching model. These assumptions are based on the pronounced reaction of equity markets to negative shocks (Kang, Ratti, & Yoon, 2015; Ding, Granger, & Engle, 1993) and the fat-tails of the distribution (Jondeau & Rockinger, 2003). A two-state Markov regime switching model is specified as in Haas et al. (2004a) thus:

$$y_t|(s_{t-1} = k, I_{t-1}) \sim S(0, h_{t,1}, v)$$

$$h_{k,t} = \alpha_{0,k} + (\alpha_{1,k} + \alpha_{2,k}\, \mathrm{II}_{\{y_{t-1}<0\}})y_{t-1}^{\ 2} + \beta_k h_{k,t-1},$$

with $k \in \{1,2\}$ and II an indicator function which takes the value one if the condition is true and zero otherwise. Hardy (2001) studied regime switching extensively in equity markets and found that two regimes adequately describe the market volatility dynamics. The model is built using the R package MSGARCH of Ardia et al. (2017) built on the R statistical language platform (R Core Team, 2016). The results are displayed in Tables 1 and 2.

Table 1: Results of the MS-GARCH model with two regimes

	Mean	SD	SE	TSSE	RNE
$\alpha_{0,1}$	0.0009	0.0009	0.0001	0.0001	0.1503
$\alpha_{1,1}$	0.0312	0.0095	0.0003	0.0005	0.3082
$\alpha_{2,1}$	0.0005	0.0007	0.0002	0.0007	0.1936
β_1	0.7531	0.0557	0.0016	0.0035	0.2003
υ_1	94.0962	2.0592	0.0582	0.1457	0.1598
$\alpha_{0,2}$	0.1369	0.0386	0.0011	0.0021	0.259
$\alpha_{1,2}$	0.3417	0.0836	0.0024	0.0041	0.3335
$\alpha_{2,2}$	0.0842	0.0388	0.0011	0.0027	0.1599
β_2	0.5471	0.098	0.0028	0.005	0.3115
υ_2	15.457	3.7623	0.1064	0.2248	0.2242
P_{11}	0.4421	0.0489	0.0014	0.0022	0.3837
P_{21}	0.4188	0.0413	0.0012	0.0022	0.295

Table 2: Transition matrix

	t+1|k=1	t+1|k=2
t+1|k=1	0.4421	0.5579
t+1|k=2	0.4188	0.5812

Table 3 shows the results of the 95% posterior intervals for the estimated parameters of the model. The intervals computed for $\alpha/2$ equal-tails shows all the parameters to be significant.

Table 3: 95% Bayesian credible intervals of the parameters

Parameters	2.50%	97.50%
$\alpha_{0,1}$	0.00004	0.00321
$\alpha_{1,1}$	0.01631	0.05267
$\alpha_{2,1}$	0.00012	0.00222
β_1	0.62491	0.83881
υ_1	89.70408	97.59313
$\alpha_{0,2}$	0.07266	0.22588
$\alpha_{1,2}$	0.20253	0.53275
$\alpha_{2,2}$	0.03153	0.18311
β_2	0.34078	0.72150
υ_2	9.67035	24.65909

The results of the parameter estimates point to the heterogeneity in the evolution of the volatility across both regimes. Regime 1's degrees of freedom is 94 compared with 15 for Regime 2. This shows that the second regime is heavy-tailed. The estimated annualised unconditional levels of volatility are 6.40% and 15.73% confirming the presence of a relatively low and high regime respectively. The conditional probability of finding itself in Regime 1 and Regime 2 is respectively 42% and 53%. Figure 5 shows that the high volatility regime bursts briefly from time to time. The low regime dominated trading days for much of 2014 to the end of 2016. The regimes have different reactions to past negative returns. Regime 1 has a past negative reaction of 0.0145 and regime 2's reaction is 0.0394 showing a heightened response to past negative shocks. This is in line with regime two's high unconditional volatility. Result from the transition matrix is shown in Table 2. Figure 5 shows annualised volatility. It is seen from the figure that volatility is high near the end of the year to the beginning of the following year. The market has been generally quiet from the second quarter of 2014 to the end of 2016.

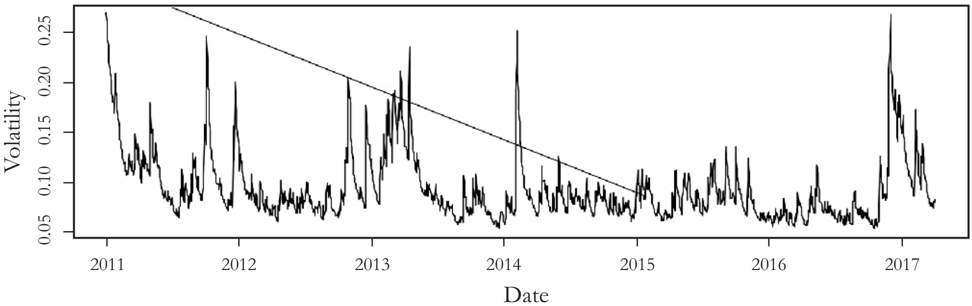

Figure 5: Evolution of volatility GSE All Share Index through time

The persistence of the volatility is given by $\alpha_{1,k} + ½\alpha_{2,k} + \beta_k$ where $k \in \{1,2\}$ is 0.7848 for regime 1 and 0.973 for regime 2. This shows the higher persistence of volatility for regime 2. Overall, for the period studied, the results show regime 1 in which the unconditional volatility of low with equally slow negative reaction to past news and relatively low persistence of volatility. In contrast, regime 2 is characterised by high volatility persistence, a high unconditional volatility period and relatively to regime 1, a swift negative response to past news. For investors, regime 2 offers both opportunity and risk in the trading process. They have to layer their trading and investments with strategies that mitigate the turbulence associated with trading in such periods.

To compare the annualised unconditional volatility of the returns of GSE index with the returns of some developed and emerging world equity markets, we downloaded data for the S&P 500 (US), CAC (France), DAX (Germany), Nikkei (Japan) and Hang Seng (Hong Kong) from Yahoo! Finance for the same period January 04, 2011 to March 31, 2017 and subjected them to the same two-regime GJR-GARCH with student-t innovations. Table 4 displays the unconditional volatility for the two regimes of the markets.

Table 4: Comparison of some developed and emerging market unconditional volatility with GSE

	CAC	S&P 500	DAX	Nikkei	Hang Seng	GSE
Regime 1	15.14%	11.40%	7.16%	20.79%	16.14%	6.40%
Regime 2	33.65%	17.25%	25.01%	31.01%	54.27%	15.73%

The annualised unconditional volatility of the returns of the GSE All Share index is low in both regimes examined for the period. Compared with the Hang Seng, an emerging market index of the Hong Kong equity market, the GSE index being a frontier market index has exhibited a rather benign volatility in both regimes. Overall, the volatility of frontier markets of SSA as represented by the GSE index is lower than some of the developed world markets.

Model Comparison

We compared our MSGARCH models with a GJR-GARCH with a *student-t* distribution assuming a single-regime. The choice of the GARCH-type and distribution of the innovations was made similar to those assumptions used in building the regime-switching model. The results of the GARCH and related parameters are shown in Table 5:

Table 5: GJR-GARCH student-t distribution parameters

	Mean	SD	SE	TSSE	RNE
α_0	0.0906	0.031	0.0009	0.0014	0.3965
α_1	0.2866	0.0648	0.0018	0.0028	0.43
α_2	0.0555	0.0485	0.0014	0.002	0.4777
β_1	0.6324	0.0654	0.0018	0.0028	0.4442
N	2.6862	0.1669	0.0047	0.0073	0.4166

The Deviance Information Criteria (DIC) of Spiegelhalter et al. (2002) of the model with regime switching and the single regime models are 2298 and 2351 respectively. This shows the former model is superior.

Model Backtesting

We backtested the MSGARCH models to assess its adequacy and quality in prediction. In backtesting the aim is to estimate whether the magnitude of losses predicted by the Value-at-Risk (VaR) is accurate to a certain significance level. We implemented the conditional coverage test of Christoffersen (1998) which tests for both the number of exceedances and clustering of these exceedances. The competing test of Kupiec (1995), that is the unconditional coverage, does not take the clustering of VaR violations into consideration. In risk modeling we are interested in these clustering events as they are more likely to lead to extreme market volatility for days in a row and increasing the risk of bankruptcy. Empirically, clustering of volatility has a direct linkage with increase in market volatility; hence the conditional coverage is the appropriate test as it tracks the changes in data, especially where such changes are large, over time.

The likelihood ratio test of the conditional coverage (LR_{cc}) is distributed as $\chi^2(2)$ with the hypothesis stated as follows:

H_0: correct conditional coverage
H_a: incorrect conditional coverage.

The test was conducted with a specified 5% significance level. We obtained a p-value of less than 0.4130844, hence we fail to reject the null hypothesis. Thus, we conclude that the MSGARCH model is correct on average.

Conclusion

Volatility in frontier markets is has been said to be higher than that in the developed markets (Kiviaho, Nikkinen, Piljak, & Rothovius, 2014). We have shown that for sub-Saharan African frontier equity markets, that is not necessarily the case. Also, we have shown the superiority of the regime-switching GARCH model over the classical GARCH in describing the evolution of the heteroscedastic dynamic over the sample period.

By incorporating regime switching into estimating volatility, we have provided investors an important tool to support investment decision-making about the markets studied. Macro investors have to identify the drivers of risk within the high volatility regimes and build trading strategies to counter and even profit from the dynamics in the market. A lack of full understanding of frontier market risk dynamics has been cited in the practitioner literature as one of the reasons why investors stay away or demand above risk returns for investing in such markets. Being able to predict to some degree of accuracy how the markets will behave in the face of such events represent a competitive advantage on its own. Regime switching models are able to capture the states of the underlying economy and how they influence the level of volatility in the equity markets. Thus investors are able to use this knowledge of the probabilities and the duration of each regime to better tailor their trading strategies in line with their risk preferences. For policymakers, both fiscal and monetary, their actions ripple through the markets and affect investor disposition to deploying their funds on the Ghana Stock Exchange. Policy actions show up in markets returns and volatility of returns in equity markets. Thus, equity markets serve as the barometer of policy effectiveness in a country. Policies should thus keep an eye on volatility of returns in the equity markets to ensure the smooth functioning of equity markets in the countries labelled as "frontier markets".

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