A Rollercoaster Ride through the Equity Markets - Evidence from the Ghana Stock Exchange

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Abstract
We investigated the presence of regimes in volatility of returns of the Ghana Stock Exchange index using single- and two-regime Markov-switching threshold GARCH with skewed- and student-t innovations separately for model fit. We found that the 2-regime threshold GARCH(1,1) with skewed student-t innovations provide a better fit to the data by using the deviance information criterion (DIC) to discriminate among the candidate models. There are two clear regimes with different statistics describing the volatility of returns for the low and high regimes. Incorporating regime switching thus avoids the practice of the single regime choice which pulverises the unconditional volatility through complex averaging leading to the overestimation and underestimation of risk during the low and high regimes respectively.

Keyword: *Regime-switching, Bayesian modeling, TGARCH, heavy tail innovations*

1. INTRODUCTION

Financial markets have been observed to exhibit strong cyclical behaviour which follows closely the business cycle of a country (Claessens, et al., 2012; Neumeyer & Perri, 2005). Developments in the underlying economy are reflected in the data generating process of the market data coming out of the country's financial especially its equity markets. As a result, any structural shifts on the economy should be mirrored in the returns of the equity index.

Economies undergo structural changes over time and such changes are nonlinear in their response to the shocks buffeting an economy. Thus, different time series which are nonlinear, are required to explain the empirical data at different times or states of the economy. These states of the world or regimes can be characterised by different statistical properties with a given probability of being found in the various multiple states there are in the economy at a given time. The means, variances and covariances vary with the regimes and these have implications for investment returns and risk management. Model choice, thus, has an important bearing in capturing the changing dynamics of any statistic(s) which is regime specific.

Estimating the volatility of returns from equity markets is one of the enduring themes in financial research. To properly allocated capital in investment, risk models need to be calibrated properly to capture the regime specific conditional volatility. Marcucci (2005) recommends incorporation of regimes into volatility models for financial returns because the improve on forecasting. The other advantage, according to Klassens (2002), is that regime-switching volatility models accommodate sudden changes in the level of volatility, an important property lacking in traditional GARCH models.

Regime switching as a concept is associated with notions of the states in the economics literature. The economy undergoes transitions in response to policy directives to do with either monetary or fiscal measures. Such switching could be permanent eg. an economy adopting a free floating exchange regime or temporary as in the economy's natural expansion and contraction of economic activity around a long term trend in business cycles.

The Ghanaian economy exhibits business cycles. Ocran (2007) studied the patterns in inflation figures in Ghana for the period 1960-2003 and saw that governments in power adopt expansionary monetary and fiscal policies in the lead up to national elections and thereafter switch to contractionary policy stance when elections are over. The effects of politics in enforcing fiscal discipline are capture by Ehrhart (2013) who points out the varying efforts state institutions in developing countries put into tax collection before and after elections. Anaman and Agyei-Sasu (2012) actually found in their study a high correlation between business performance and the political transitions in Ghana. The link could be between government being the biggest consumer of the good and services provided by the listed firms and therefore their fortunes are tied to the performance of the government as hinted by Sackey and Compah-Keyeke (2012) in what they termed politico-economic cycles in Ghana. Indeed, similar observations are made in other African countries (Mosley & Chiripanhura, 2016). Given that government of Ghana is one of the biggest in terms of providing patronage of the good and services of the listed firms, any changes in the economy should affect the profitability of these firms. Investors in turn will invest in firms with strong balance sheets and good prospects of returns. All these will show as regimes in the return generation process in the equity market.

We therefore study, in this paper, whether there exists regimes in the volatility of returns in the aggregate index of the Ghana Stock Exchange. We applied four difference models, two being regime switching and the other two single regime models, to fit the returns of the Ghana Stock Exchange index (henceforth GSE index). In all cases, we tried student-t and skewed student-t innovations, a choice informed by the distribution of the returns.

We used data spanning the sample period January 04, 2011 to March 31, 2017 in the study. We corrected the returns for thin and asynchronous trading observed in Ghanaian and Nigerian equity markets by Mlambo and Biekpe (2005). Our findings are as follows. There exists clear regimes in the volatility of returns of the GSE index with differing volatility dynamics across the regimes. The unconditional volatilities of the low and high regimes are 4.61% and 18.78% respectively. Of the four volatility models fitted to our returns, the Bayesian Markov-switching threshold GARCH(1,1) with skewed student-t innovations provided a better fit. We used the deviance information criterion as a selection criteria from among the candidate models.

This paper adds to the growing literature on modeling volatility of returns of the Ghana Stock Exchange index by using an asymmetric Bayesian Markov-switching threshold GARCH to capture the behaviour of the volatility of returns of the aggregate market index. To the best of our knowledge and the review of the literature in finance and economics, this paper is pioneering in its use of the Bayesian Markov-switching threshold GARCH incorporating skew and heavy tails in modeling volatility of the returns of the GSE index. This decision to incorporate skew and heavy tails in the modeling has been influenced by the distribution of the returns which showed marked departure from normality principally by the kurtosis which is above three. Tail risks arising out of fat tails are the famous 'Black Swan' events responsible for the implosion of hitherto storied hedge funds like LTCM, Bear Sterns and Amaranth (Ailon, 2012; Dungey, et al., 2006; Chincarini, 2007). McNeil and Frey (2000) and Gençay, Selçuk and Ulugülyağci (2003) underscored the important of tails in risk models. The presence of heavy tails in return distributions signals the probability of extreme outcomes which represent real risks and therefore should not be ignored in volatility modelling. Researchers understate risk when they ignore the distribution in the tails. This has a serious implications for risk management strategies. On so many levels, that is the important lesson academics and practitioners have learned from the global financial crisis of 2007-2009 (Nelson & Katzenstein, 2014; Aloui, et al., 2011). By making provision for the tails of the distribution of returns, this paper captures the true evolution of time-varying heteroscedasticity of financial returns in equities for investors to adequately manage the resulting risks.

The paper, in incorporating regime switching into the model, is a departure from the existing stream of research on volatility models on the GSE index returns. There are lots of papers on the volatility modeling of GSE index returns; see Boako et al. (2015) and Forgha (2012). None of these incorporated regime switching into their analyses. Finance, at its core, is about managing and controlling risk. Incorporating regimes into the volatility modeling process is no longer trivial in finance. Risk switches through different levels over time and for optimal allocation of capital in the face of uncertainty, regimes in the data generation process should be accounted for. Marcucci (2005) provides results to support the use of regime switching in modeling the volatility of financial time series.

The rest of the paper evolves as follows. Section 2 of the paper reviews the literature on modeling volatility using Markov regime-switching GARCH models. We formally lay out the model in section 3. Data, analysis and discussion goes into section 4. Finally, section 5 concludes the paper.

2. LITERATURE

The time series finance literature has identified two approaches for modeling 'states' of the evolution of financial variables. They are either the regimes switching between states based on unobserved components, giving rise to the Markov regime-switching (MRS) models introduced by Hamilton (1994) or observed components leading to Threshold type Autoregressive (TAR) models popularized by Tong (1980). The work on the MRS model was expanded in Hamilton (1990) and Hamilton and Susmel (1994). They were mainly motivated by the October 1987 market crash in the US. Among other reasons, external shocks such as high crude oil prices for both importing and exporting economies, a slump in the world prices of commodities, major government policy changes, political upheavals and the regulatory environment for conducting business have been identified in the finance literature as the triggers of regime switching in the financial markets. For example economic shocks arising from crude prices are known to affect equity markets through regime switching from a period of low return/high volatility regime to high return/low volatility regime (Aloui & Jammazi, 2009; Choi & Hammoudeh, 2010).

This phenomenon has been studied extensively in developed and emerging markets and across different asset classes. Klaassen (2002) sought to incorporate regime switching into GARCH models to improve the predictive power of the latter as they capture the transitions and various states of volatility models. For the developed markets, notable work was done by Hardy (2001) in studying the S&P 500 and the TSE 300 equities and established the presence of regimes in the US and Canadian equities.

Wang and Theobald (2008) studied the emerging equity markets of six East Asian economies over the period from 1970 to 2004 and found evidence of regime switching following the liberalization of those economies. Numerous other studies have been carried out in the emerging markets. Aggarwal et. al. (1999) looked at the regime switching behaviour of selected emerging markets and identified the associated variation of volatility with respect to the various regimes. We then identify events around the time period when shifts in volatility occur. They found, for example, the events that drove the switching in the markets of Mexican during the peso crisis, the hyperinflation of Latin America, the Marcos-Aquino conflict in the Philippines, and the stock market scandal in India. These were characterised as local events. However, they identified the October 1987 market crash as a global event which caused significant regime switching in the states of several emerging stock markets.

Regime switching has also been used extensively to explain market contagion during financial crises. For example Guo et. al. (2011) relied on a Markov regime switching VAR framework in studying the spread of contagion effects across the stocks, real estate, credit default and energy markets in the US following the global financial crisis. The volatility in one market cascades through the other markets through fear.

Ang and Timmermann (2012) point out that the various market regimes are clearly defined with different means, volatilities, autocorrelations, and cross-covariances of asset returns, allowing researchers to delineate and model the stylized behavior of many financial series including regime-specific fat tails, heteroscedasticity, skewness, and time-varying correlations. Probabilistically, regime switching in the data generating process can be seen as providing the fit to data in the presence of unobserved heterogeneity in which distinct clusters, each with its own set of statistics, occurs. It is intuitive that regime-switching models follow logically from change in the underlying economic environment and subsequent to that, a change in the data generating processes of related financial variables.

Several advantages are associated with GARCH models incorporating regime-switching in modeling. Regime-switching models are remarkably good at capturing conditional heteroskedasticity in long term studies, something GARCH models are unable to do. Bibi and Ghezal (2018) observed that regime-switching models provides better volatility forecasts than either a constant-variance or a single-regime GARCH. This confirms earlier work by Klaassen (2002). In numerous studies, researchers accounted for sudden swings in the volatility of financial variables using regime-switching models. It has been used to study the regime dependent volatility in commodity markets (Alizadeh, et al., 2008), interest rates (Garcia & Perron, 1996), business cycles (Filardo, 1994) and many more financial variables. Studies in equity markets both in developed and developing markets abound (Schaller & Norden, 1997; Lamoureux & Lastrapes, 1990; Aggarwal, et al., 1999; Walid, et al., 2011). This provides the motivation for studying the volatility of the GSE index using the MS GARCH.

3. MODEL

Consider that we have a vector of de-meaned stationary returns $\{r_t\}_{1\leq t\leq T}$. The guiding model of regime switching based on unobserved components is due to Hamilton (1994). It starts by partitioning the times series in k non-overlapping periods. These represent the regimes which are piecewise linear approximations of the general nonlinear model. For this we write the threshold GARCH(1,1) of Zakoian (1994) as:

$$r_t = \sigma_t \varepsilon_t$$

$$\sigma_{k,t}^{1/2} = \alpha_{0,k} + \left(\alpha_{1,k}\mathbb{I}_{\{y_{t-1}\geq 0\}} - \alpha_{2,k}\mathbb{I}_{\{y_{t-1}<0\}}\right)y_{t-1} + \beta_k \sigma_{k,t-1}^{1/2}$$

for $k = 1, . . . , K$ being the regimes. ε_t refers to the independent and identically distributed innovations with mean zero and variance one ie. $\varepsilon_t \sim \text{iid}\mathcal{D}(0,1)$. σ_t is the conditional variance of returns given the filtration I_{t-1}. The parameters $\Theta_k = \{\alpha_{0,k}, \alpha_{1,k}, \alpha_{2,k}, \beta_k\}$ is to be estimated. We impose the restrictions $\alpha_{0,k} > 0, \alpha_{1,k} > 0, \alpha_{2,k} > 0, \beta_k \geq 0$ to ensure the volatility $h_{k,t}$ is strictly positive.

Francq and Zakoian (2011) state the condition for covariance-stationary in each regime as $\alpha_{1,k}^2 + \beta_k^2 - 2\beta_k(\alpha_{1,k} + \alpha_{2,k})E\left[\eta_{t,k}\mathbb{I}_{\{\eta_{t,k}<0\}}\right] - \left(\alpha_{1,k}^2 - \alpha_{2,k}^2\right)E\left[\eta_{k,t}^2\mathbb{I}_{\{\eta_{k,t}<0\}}\right] < 1$.

3.1 Model Estimation

Estimation of models parameters is via either maximum likelihood (ML) estimate or MCMC. In both approached, we evaluate the likelihood given by:

$\mathcal{L}(\Omega|r) = \prod_{t=1}^{T} f(r_t|\Omega, I_{t-1})$,

with $f(r_t|\Omega, I_{t-1})$ as the density of r_t given the filtration I_{t-1} and the vector of model parameters Ω. The Markov-switching GARCH conditional density for the returns, r_t, is specified as follows:

$$f(r_t|\Omega, I_{t-1}) = \sum_{i=1}^{K}\sum_{j=1}^{K} p_{i,j}\lambda_{i,t-1} f_D(y_t|s_t = j, \Omega, I_{t-1})$$

where $\lambda_{i,t-1} = P(s_{t-1} = i|\Omega, I_{t-1})$ is the filtered probability of regime i at a time t-1. There are practical difficulties estimating MSGARCH models via ML. MSGARCH models are path dependent; hence there is the tendency for the estimation to get stuck in a local maximum giving unreliable estimates (Billio & Cavicchioli, 2017). We therefore maximise the log-likelihood by following the method of Ardia (2008). We draw samples from the posterior generated with the adaptive random-walk Metropolis sampler of Vihola (2012). Our inferences about the estimates are based on the resulting posterior sample distribution.

4. DATA AND RESULTS

4.1 Descriptive Statistics

We used GSE All Share index data for the period January 01, 2011 to March 31, 2017. A plot of the series is shown in Figure 1.

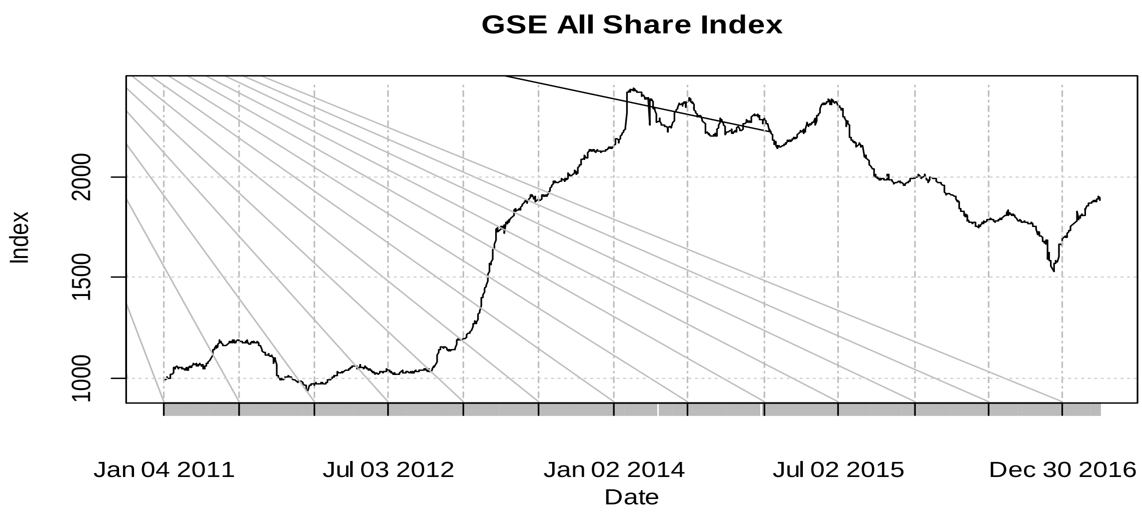

Figure 1: Time series of the GSE index

There is a bump in the level of the index in the latter part of 2011 and then remaining flat for much of 2012 before trending up, eventually peaking at the beginning of 2014. From there the level trended downwards with the occasional bump in July 2015, low a low at the end of 2016 before the market turned bullish from the beginning of 2017.

A plot of the distribution is shown in Figure 2. The normal distribution and density curve were overlaid on the histogram. The graph shows deviations from normality. This is confirmed by the statistics in Table 1.

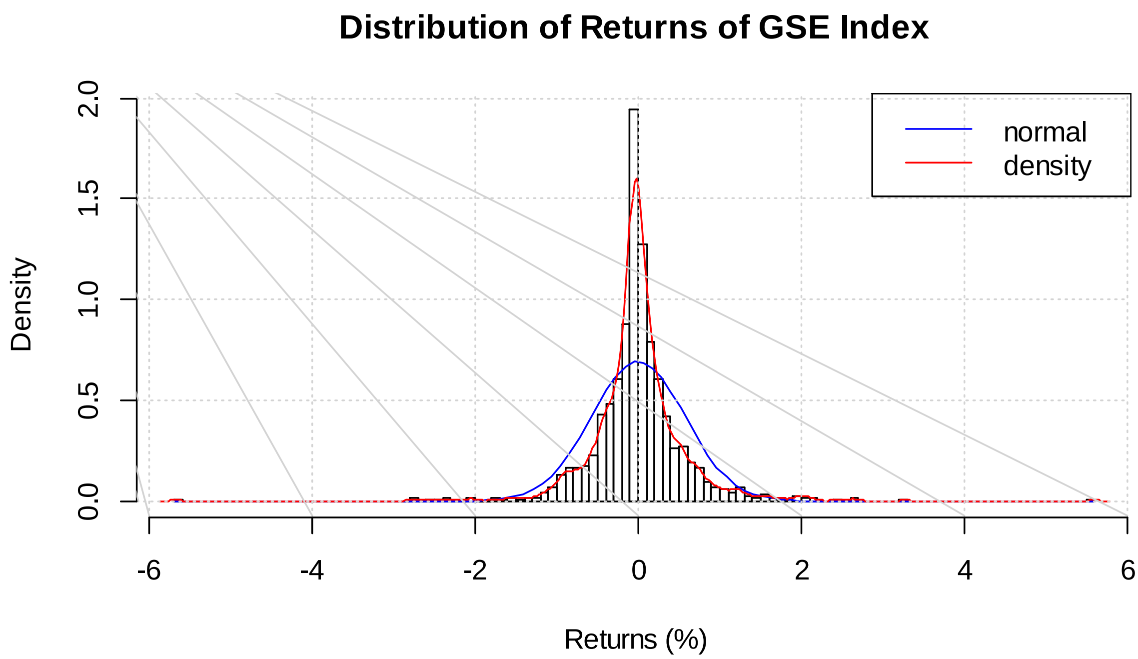

Figure 2: The distribution of the returns of the GSE index returns

Table 1: Some statistics from GSE index returns

Statistic	Mean	Sd	Median	min	Max	Skew	Kurtosis
Value	0	0.58	-0.03	-5.68	5.6	0.29	15.47

The distribution is heavy-tailed as indicated by the kurtosis of 15.47 and also slight skewed to the right. This is in line with the findings of Cont (2001) who showed that heavy-tails characterise returns on equities. We tested for normality by performing the Jarque-Bera test. At the 0.05 significance level, we had a p-value of almost zero; hence we reject the null hypothesis of normality and conclude that the distribution is not normally distributed.

We calculated the log-returns from the relation $r_t = \log P_t - \log P_{t-1}$. These returns, r_t, were demean and converted to percentages to prevent numerical round-offs of small values. A plot of the returns r_t of the index is shown in Figure 3. Visually, there is no trend suggesting stationarity of the returns.

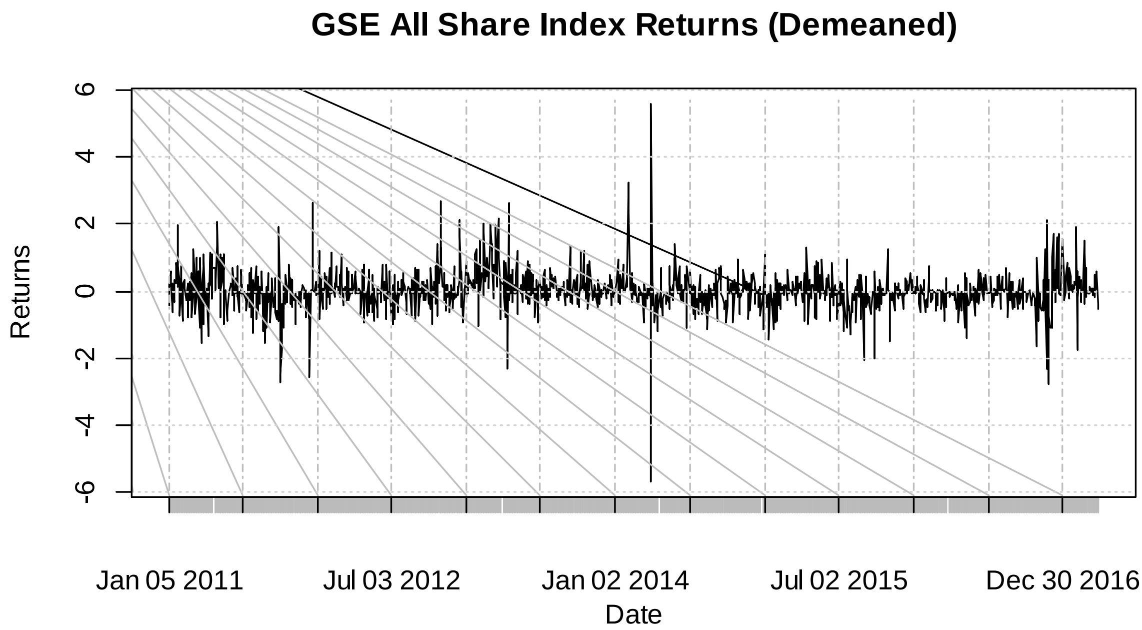

Figure 3: A plot of the GSE index returns

We confirmed stationary through the augmented Dickey-Fuller test which gave us a p-value of 0.01. This value is less that 0.05; hence we conclude that our return series is stationary.

To build the GARCH model, we have to establish the presence of (G)ARCH effects in the data. We employed Engle-LM test which regresses the residual of the returns on its lagged values. The test gave a χ^2 = 297.32 with 12 degrees of freedom and p-value less than our cut-off point of 5%. We therefore reject the null hypothesis of no (G)ARCH and conclude the presence of these effects.

4.2 Estimation of TGARCH models

We estimated the Bayesian threshold TGARCH(1,1) parameters for four threshold GARCH models in order to compare model fit. We have the two-state TGARCH with skewed student-t innovations, two-state TGARCH with student-t innovations, single-regime TGARCH with skewed student-t innovations and single-regime TGARCH with student-t innovations. On each occasion we specified 12500 iterations with a burn-in of 5000. Raftery and Lewis (1992) recommended that at least a burn-in of 4000 be used. We thinned at every tenth to reduce the autocorrelations in the posterior draws. High autocorrelations do bias the resulting Monte Carlo standard errors. A number of authors, though, have raised concerns about the appropriateness of thinning; see Owen (2017); Link and Eaton (2012); Geyer , 1992 for discussions. The resulting graphs of the conditional volatility is shown in Figure 4. It is difficult to tell visually which of the models fits the data adequately.

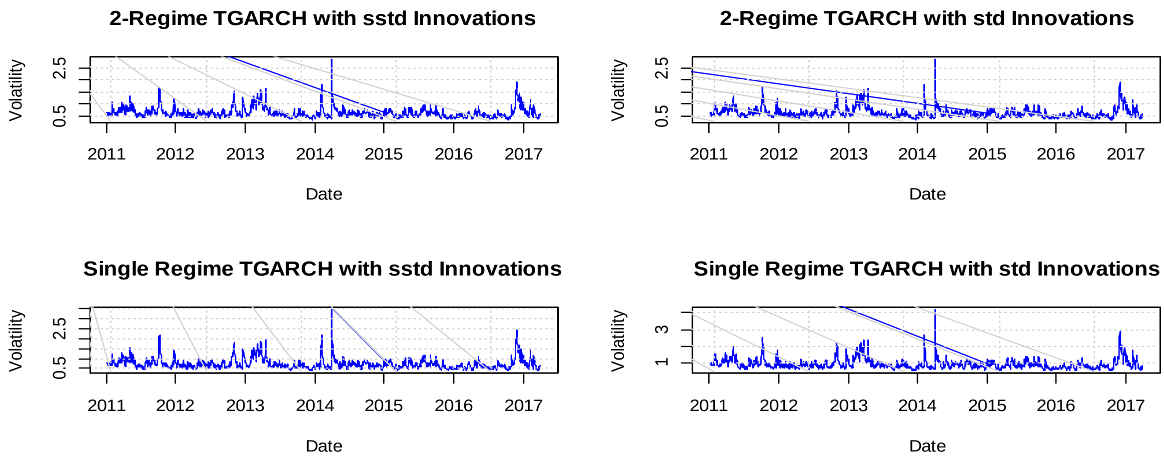

Figure 3: Conditional volatility of TGARCH(1,1) with sstd and std innovations

We therefore extracted the Deviance Information Criteria (DIC) due to Spiegelhalter et al. (2002). These are shown in Table 2.

Table 2: Comparative DIC of the models

Model	DIC
2-state TGARCH with skewed student-t innovations	2040.43
2-state TGARCH with student-t innovations	2047.59
Single-state TGARCH with skewed student-t innovations	2099.28
Single-state TGARCH with student-t innovations	2104.54

It is clear that the two-state models with the skewed student-t innovations provides a better fit to our data. This confirms our observation of the skewed distribution with heavy-tails of the returns shown by the histogram in Figure 2.
The unconditional volatility of the models is shown in Table 3.

Table 3: Unconditional volatility of the models

Model	Regime 1	Regime 2
2-state TGARCH with skewed student-t innovations	4.61	18.77
2-state TGARCH with student-t innovations	4.25	17.067
Single-regime TGARCH with skewed student-t innovations	15.79	NA
Single-regime TGARCH with student-t innovations	14.27	NA

*NA stands for not applicable
The two-state regimes clearly distinguish the volatility dynamics in the respective regime. The single regime models pulverises the volatility of the regimes giving us a seemingly complex weighted average that does not reflect the true risk from regime to regime. Relying on the volatility figures given by the single-regime volatility models will grossly over estimate risk in regime 1 leading the misallocation of capital. This is even severe considering that we are in regime 1 for 54% of the time compare with 46% in regime 2.
I did a posterior predictive check examining convergence of the MCMC chains by employing the trace and density plots of the parameters of the two-regime TGARCH with skewed student-t innovations. This is shown in Figure 4.

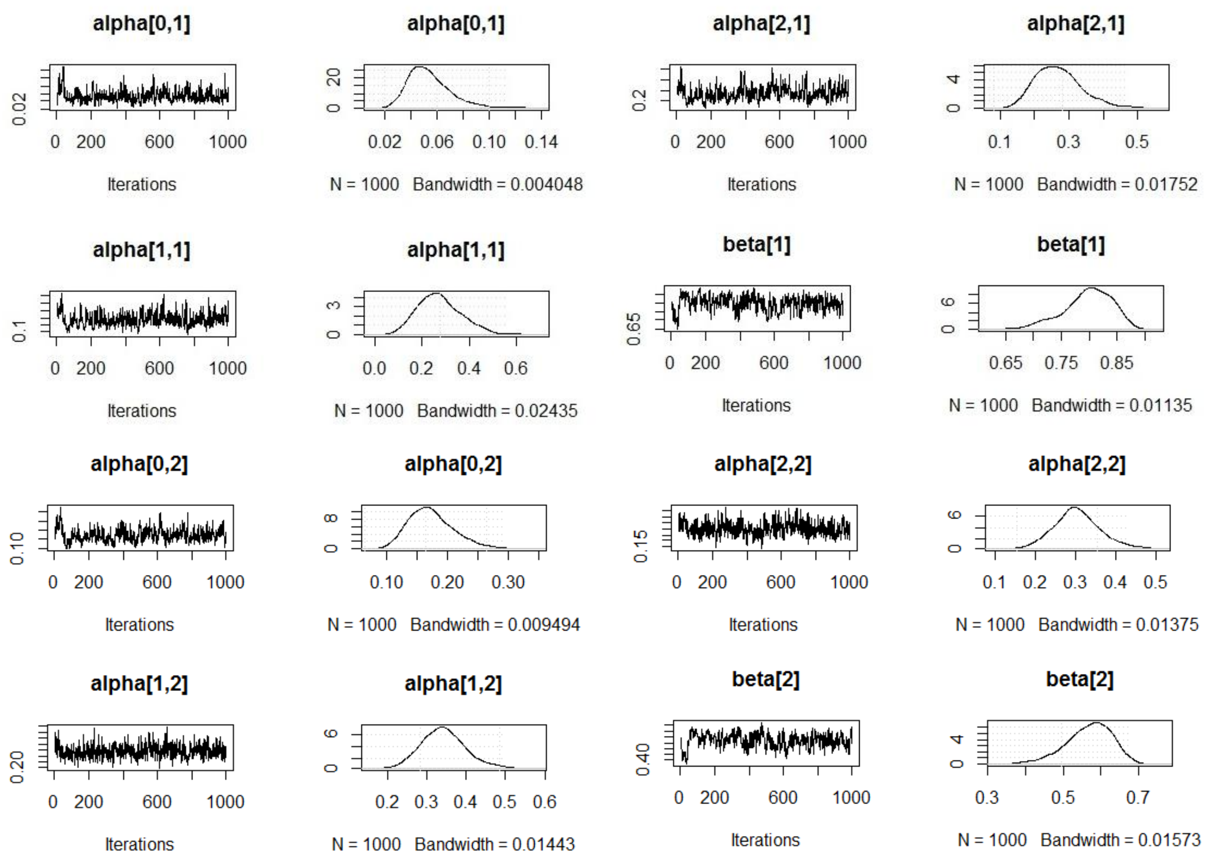

Figure 4: Trace and density plots of estimated parameters of 2-regime TGARCH with sstd innovations

The trace plots show the Markov chains are stationary; hence they converge to the posterior distribution. The acceptance rate from the MCMC sampler is 27.8%. This is within the range of 20%-50% 'rule of thumb' acceptance rate recommended by some authors (Roberts & Rosenthal, 2009; Chib & Greenberg, 1995).

Table 4: Parameter estimates of 2-regime TGARCH with sstd innovations

Estimate	Mean	SD	SE	TSSE	RNE
α_0^1	0.0547	0.0165	0.0005	0.0014	0.1312
α_1^1	0.2765	0.0924	0.0029	0.0079	0.1382
α_2^1	0.2702	0.0662	0.0021	0.0057	0.1358
β_1	0.7973	0.0426	0.0013	0.0052	0.0666
ν_1	2.1	0.0037	0.0015	0.0006	0.2032
τ_1	1.0602	0.0334	0.0011	0.002	0.2677
α_0^2	0.1739	0.036	0.0011	0.0037	0.0943
α_1^2	0.342	0.0545	0.0017	0.0032	0.2948
α_2^2	0.3035	0.0558	0.0018	0.0038	0.2212
β_2	0.568	0.0591	0.0019	0.0069	0.0726
ν_2	93.2916	1.2524	0.0396	0.0838	0.2233
τ_2	1.2332	0.1117	0.0035	0.0064	0.3041

One thing that is immediately clear from Table 2 is the distribution of returns on the respective regimes. Regime 2 has its degrees of freedom $\nu_2 = 93.2916$ showing the existence of heavy-tails compared with $\nu_1 = 2.1$ of the relatively thin tails of regime 1. The relative numerical efficiency (RNE) indicates the number of draws that would be required to produce the same numerical accuracy if the draws had been made from an independent and identically distributed sample directly from the posterior distribution. It is a proxy for how quickly the algorithm converges. Geweke (1991) recommends its use as a check on the quality on the MCMC sampling scheme. Values of RNE below one are better. The values in Table 4 are relatively low. This indicates faster converge of the MCMC chains.

Table 5: 95% credibility intervals of estimates

Estimate	2.50%	97.50%
α_0^1	0.0301	0.0940
α_1^1	0.1256	0.4694
α_2^1	0.1666	0.4136
β_1	0.7025	0.8642
τ_1	0.9981	1.1304
α_0^2	0.1173	0.2557
α_1^2	0.2473	0.4637
α_2^2	0.1995	0.4228
β_2	0.4402	0.6652
τ_2	1.0394	1.4683

The Bayesian posterior intervals calculated from the posterior distribution for the 2.5% and 97.5% quantiles show all the estimates a credible. This is because the estimates are regime specific unlike the single-regime which pulverises these estimates. The 95% posterior intervals for the threshold parameters τ_1 and τ_2 do not contain zero showing significance of the thresholds. We observe asymmetric persistence in market volatility as indicated by the different values for the persistent parameters given for regime 1 and regime 2 respectively as $\beta_1 = 0.7973$ and $\beta_2 = 0.568$.

5. CONCLUSION

Sustained low volatility and low yields in the developed markets since the global financial crisis of 2008-2009 have pushed more investors to venture into far flung places in search for investment opportunities. Lots of investments are pouring into frontier markets including Ghana. However, it is reported in the practitioner literature mainly (Kidd, 2013) that frontier markets are fraught with elevated market risks. Investors characterise frontier market economies as fragile, suffering from episodes of civil unrest and strikes that destabilise and disrupt financial and economic activities. That aside, it is known that financial markets in frontier economies, are tightly anchored to the underlying economy through the listed firms' reliance on the public sector for the patronage of their goods and services. This therefore should show up as regimes in the returns of equities. Given the changes the underlying economy goes through in Ghana, we suggest that any model that aims at capturing the heteroskedasticity in the broader financial markets should incorporated regime-switching.

This study has, indeed, identified the regimes in the GSE index returns and the probabilities of the market being in a given regime. No doubt, this is essential to investment and risk management. The risk-on, risk-off effect of volatility represent opportunities for sound trading by combining financial instruments to hedge one's trading positions on the GSE. For policymakers, this study will serve as a gauge of the barometer of the market. They have to look out for the periods during which policies in the underlying economy induces disruptive high volatility in the stock market. Orderly flow of trading activities devoid of extreme high volatility, especially in relatively young markets, is essential for investor confidence and investment activities.

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