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Behaviour of Johannesburg Stock Exchange All Share Index Returns - An Asymmetric GARCH and News Impact Effects Approach

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Abstract

We investigated the behaviour of returns of the Johannesburg Stock Exchange All Share Index using asymmetrical exponential-GARCH(1,1) and GJR-GARCH(1,1) incorporating the market reactions to news. We noted the returns distribution is skewed and have fat-tails with respect to the normal distribution. Thus we chose the skewed student t-distribution asymmetry to model the behaviour of the tails and capture the asymmetry in the distribution of the returns. The GJR-GARCH(1,1) with the skewed student t-distribution was found to be appropriate in describing the data generation process for the returns. The market was shown to react to news unequally. Volatility spikes sharply when unexpected adverse news reaches the market while remaining unresponsive for a large part to positive news. For investors this has implications for trading strategies and risk management with respect to equity portfolio risk and returns on the stock exchange. Bad news reaching the market can destabilize their portfolios. Risk mitigating actions by way of 'hedging' against the noise in the news is warranted.

Keywords: Backtesting, E-GARCH, GJR-GARCH, Volatility, News Impact
JEL Classification: C01, C5, C58

1. Introduction

Day-to-day volatilities in returns is a measure of the uncertainty in short term monetary policies in many economies; such policies moderate or spur economic activity in the South African economy as well. Investors shift resources in and out of the stock market or within the same market but in different financial instruments which is reflected in the changing levels of the index and hence the volatility. Such volatility could be a course of interest rate fluctuations shifting the attractiveness of asset classes on the stock market for investors with a focus on short-term profits. In a period of rising share prices, individuals pile up into the stock markets with more money when prices are up and less so when prices are down. Invariably this correlates closely with developments on the underlying economy. Investing in stock markets is a sign of confidence in the economy.

Forecasts in investment are invariably risk based. Risk is ever present on the minds of investors as it is a crucial predictor of unfavourable events with adverse consequences in terms of portfolio exposure. Volatility, having become synonymous with risk, lends itself to a lot of importance in empirical finance; particularly, its correlation property. The expanse of literature on volatility perhaps surpasses any singular real concept in finance; largely because of its pervasiveness and impact on assets and markets alike. Investors and analysts alike must be wary of not just risk but also the data generating process of volatility in order to make sound data-driven decisions.

The exponentially weighted moving average (EWMA); an extension of the historical average volatility measure, is the initial attempt at capturing volatility dynamically; the result of work done by J.P. Morgan in RiskMetrics (Morgan, 1996; Pafka & Kondor, 2001). EWMA is an improvement in the constant weighted moving average (MA) which failed to capture the volatility clusters (which makes volatility such a fascinating concept) in the return series of stock markets.

A cursory look at financial data plots suggests that some time periods are riskier than others; thus, however widespread, the assumption that returns are independent and identically distributed (i.i.d) and implicit in the EMWA, volatility and correlation forecasts that are made from these models are simply equal to the current estimates is very unrealistic. These risky times are not scattered randomly across daily, quarterly or annual data. Instead, there is a degree of autocorrelation in the riskiness of financial returns. The autoregressive conditional heteroscedasticity (ARCH) introduced by Engle (1982) and generalised autoregressive conditional heteroscedasticity (GARCH) by Bollerslev (1986) have become widespread tools for dealing with time series heteroscedasticity. The goal of such models is to provide a volatility measure – like a standard deviation, that can be used in financial decisions concerning risk analysis, portfolio selection, and derivative pricing.

The forecasts that are made from these models are not equal to the current estimate. Instead volatility can be higher or lower than average over the short term but as the forecast horizon increases the GARCH volatility forecasts converge to the long-term volatility. Put another way, the GARCH model captures volatility clustering (Alexander, 2008; Engle, 2001).

Over the years GARCH – regarded as the parsimonious form of the ARCH model has become the workhorse of empirical volatility study. However, the diversity in the GARCH models poses another important question as to which specific variant of GARCH is appropriate tool for the investor or the analyst in a specific market. In this work, we put ourselves in the shoes of the investing public and ask: what is the best model that describes the data generating process for the volatility of the Johannesburg Stock Exchange All Share Index returns and what is the impact of unexpected news on the level of volatility in the market? Answering these questions would help to identify, provide in-depth insight, and appropriately establish strategies in the decision environment of trading will provide a safe harbour for investor in an ever-changing equity market.

Alagidede (2011), Collins G. Ntim et al. (2011), and Appiah-Kusi & Menyah (2003) found evidence of predictability of both returns and volatility of African equity markets. By implication these markets are inefficient. We are of the view that volatility hence returns of the markets will be conditionally varying in the light of recent global upheavals in developed world markets forcing investors to look beyond their borders into far-flung markets for new opportunities. Thus with new actors in the markets, the same stylized factors observed in the developed markets could be in place in the emerging markets of which the Johannesburg Stock Exchange falls under. Moreover, similarities in regulatory and structural frameworks across stock markets make this research on the JSE worthy of execution. Our work therefore is a departure from the notion of inefficient markets enabling predictability to one of efficiency where we see stochasticity of these moments in the market using the exponential-GARCH(p,q) (EGARCH) and GJR-GARCH(p,q) models based on data comes from the Johannesburg Stock Exchange All Share Index spanning the years 2003 to 2015.

Volatility of returns fluctuates over time contrary to the assumptions of independent and identically distributed with constant variances as found in most financial models. Characteristics like nonnormalities, clustering and structural breaks in financial data are difficult to capture with conventional distributions (Engle & Patton, 2001; Wang et al., 2001). Heavy- or fat-tails of the distributions with higher than normal probabilities particularly of losses in the left tail can surprise investors as happened on Black Monday October 19, 1997 when the market crashed (Amihud et al., 1990; Schwert,1989). Thus our need to use the EGARCH(p,q) and GJR-GARCH(p,q) in the family of asymmetric GARCH models in this work.

Piesse & Hearn (2002) studying African markets integration, suggest that the univariate EGARCH models by Nelson (1991) are appropriate for the analysis of African market since they can successfully model asymmetric impacts of good news (market advances) and bad news (market retreats) on volatility transmission with high levels of accuracy. The GJR-GARCH(p,q) models are in the same family of asymmetric GARCH models. Other studies on African markets include Tooma (2003) for Egypt and Alagidede & Panagiotidis (2006) used both daily and monthly stock data to examine calendar anomalies (day of the week and month of the year effects) in the GSE; they employed non-linear models from the GARCH family in a rolling framework to investigate the role of asymmetries arriving at the threshold GARCH (TGARCH) as the best model.

The remainder of this paper is as follows: Section 2 reviews relevant literature for the models used in herein followed by methodology in Section 3. Section 4 presents the data and estimation results, and we end with the conclusion in Section 5.

2. Literature Review

Volatility of major asset classes is an important input in investment portfolios. Generally it is seen as a measure or gauge of the fear level in the market. When assets prices decrease in the equity markets, volatility spikes. This is a reflection of the negative correlation between assets prices and volatility. Unlike the prices of market securities which can be observed directly in the markets, volatility is a latent variable that is computed from the returns of the securities or inferred from model-based market prices of derivative instruments. In well-developed equity markets that are operating “normally” volatilities of historical returns from equities can act as proxies for the markets going forward. Such measures give the statistical deviation (these deviations are equally weighted) of how much returns depart on daily basis from its mean over a given period. However, a graph of the returns from a market shows that volatility is not constant. There are periods of serenity in the markets in which volatility appears constant. Equally there are periods when markets are turbulent and volatility can spike and remain at that level for long in what markets term volatility clustering. Thus using historical estimates to capture such regimes will under report the volatility with respect to ex ante decision-making whether in pricing the myriad of financial instruments, making security selection decisions, or calculation of value-at-risk measures in modern risk management.

On the other hand is implied volatility derived from the traded prices of derivative contracts written on stocks using a model. One such model is the Black-Scholes Black & Scholes (1973) option pricing model for pricing calls and puts. Where such data is available, the volatility derived reflects the current market sentiment and expectation. Implied volatility is typically not flat as it reflects the market participants buy and sell decisions which can be influenced by a range of factors. It is known that market actors have problems deciphering the true meaning of these factors in most cases. Indeed Jorion (1995) found ample evidence that implied volatilities derived from models can have substantial biases. Fleming (1998) also documents biases in the estimation of the implied volatilities in the volatility forecasts of the S&P index option prices. Still other researchers have criticised the implied volatility as being model dependent (Choi & Wohar, 1992; Britten-Jones & Neuberger, 2000; Christensen & Hansen, 2002). Thus there are potential issues involved in relying on the implied volatilities on making ex ante investment decisions.

Both historical and implied volatility thus might not work well when markets are nervous. In quiet market conditions, both are likely to lead to the same result. But in a situation where markets are gyrating, historical volatility is likely to underestimate the true level of volatility while implied volatility is more than likely to overestimate the pulse of the market. The presence of non-negligible noise inevitably confounds the true signals related to the true behaviour of asset prices (Black, 1986). Price declines can give rise to wild volatilities alternating between sharply higher and lower levels. For instance, geopolitical developments can spur higher volatilities in the short run than in the long run. Underestimating this short-term volatility in equity markets can lead to under pricing of risks which can translate to taking positions with far reaching consequences for the investor (De Goede, 2001; MacKenzie, 2003; Carmassi et al., 2009). As a rule such a period of heightened volatility shows itself as a series of clusters on the time series plot of the returns.

Such behaviour is best modelled using the autoregressive conditional heteroscedasticity (GARCH) proposed by Engle (1982) and generalized by Bollerslev (1986). Alexander (2008) makes the claim that GARCH models provide short to medium term volatility forecasts that are based on "correctly" specified econometric models. Being a conditional volatility, the GARCH model is concerned with the evolution of σ_t^2. Unlike the historical and implied volatility, the GARCH model does not assume the returns are independent and identically distributed. This essential feature is at the heart of the time varying volatility which the GARCH model seeks to capture.

3. Methodology

That stock returns have heavy-tails and are outlier-prone (see Poon & Granger, 2003; Clements & Hendry, 2008) is a basic knowledge in finance. It is observed empirically that large negative returns tend to increase volatility than do positive returns of the same magnitude. This is the leverage effect observed in stock returns. The symmetric GARCH(p,q) which is based on the normality of the distribution is unsuitable as it fails to capture the behaviour of the tails. On this basis, Alexander (2008) recommends the use of asymmetric GARCH models for equities and commodities. We thus selected to model our returns using the exponential-GARCH(p,q) and GJR-GARCH(p,q) and comparing how they capture the idiosyncrasies in the data together with their reaction to shocks arriving in the market as news.

3.1 Exponential-GARCH

The exponential-GARCH (EGARCH) was proposed by Nelson (1991). Nelson & Cao (1992) argue that the nonnegativity constraints in the linear GARCH model are too restrictive. It makes provision for capturing the leverage effect by introducing an additional parameter γ into the GARCH model thus:

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2/\pi}\right] \quad (1)$$

where $\omega, \alpha, \beta,$ and γ are constant parameters and have their usual meaning, and from Bollerslev (1986) generalisation of the ARCH(p) to the GARCH(p,q):

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}, \quad (2)$$

where $\alpha_1, \dots, \alpha_p, \beta_1, \dots, \beta_q,$ and ω are constant parameters (Engle & Ng, 1993).

The conditional variance is constrained to be non-negative by the assumption that the logarithm of h_t is a function of past values of ε_t^2. Given the error process parameterised as:

$$\varepsilon_t = \varepsilon_{t-1}^2 (h_t)^{1/2}, t = 1, \dots, T \quad (3)$$

From (1) we see γ being a function of both the magnitude and sign of ε_t^2 which enables h_t to respond asymmetrically to positive and negative values of ε_t, believed to be important for example in modelling the behaviour of stock returns.

The model in (1) captures the asymmetry in the returns distribution because of the multiplicative term $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$. The coefficient γ is typically negative. That ensures positive return shocks induce less volatility than negative return shocks (Engle & Ng, 1993). For $\gamma < 0$ negative shocks will obviously have a bigger impact on future volatility than positive shocks of the same magnitude. This effect, which is typically observed empirically with equity index returns, is often referred to as a “leverage effect”, although it is now widely agreed that the apparent asymmetry has little to do with actual financial leverage. By parameterizing the logarithm of the conditional variance as opposed to the conditional variance, the EGARCH model also avoids complications from having to ensure that the process remains positive. Meanwhile, the logarithmic transformation complicates the construction of unbiased forecasts for the level of future variances (Bollerslev, 2008). The asymmetric effect of past shocks is captured by the γ coefficient, which is usually negative, that is, cetteris paribus positive socks generate less volatility than negative shocks (Longmore & Robinson, 2004).

For EGARCH(1,1) model one can analyse the effect of news on the conditional heteroscedasticty, with a comaprison between, for instance, the GARC(1,1) model. Holding constant the information dated $t-2$ and ealier, we can examine the implied relation between ε_{t-1} and h_t called the news impact curve, with all lagged conditional variances evaluated at the level of the unconditional variance of the stock index return. The curve is so called news impact because it measures how new information is incorporated into volatility estimates, thus relating past return shocks (news) to current volatility (see Engle & Ng, 1993). The reaction of this model to news arriving in the market is given by:

$$h_t = Aexp\left[\frac{(\gamma + \alpha)}{\sigma} \varepsilon_{t-1}\right], \quad (4)$$

for $\varepsilon_{t-1} > 0,$ and

$$h_t = Aexp\left[\frac{(\gamma - \alpha)}{\sigma} \varepsilon_{t-1}\right], \quad (5)$$

for $\varepsilon_{t-1} < 0,$ and

$$A \equiv \sigma^{2\beta} exp\left[\omega - \alpha\sqrt{\frac{2}{\pi}}\right] \quad (6)$$

where σ is the unconditional return standard deviation and ω is the constant term in (2). Engle & Ng (1993) showed that the EGARCH model makes provision for good and bad news to have different effects on volatility. Though this paper is not about the evaluation of the EGARCH model it worth mentioning that prior to Malmsten (2004) it appeared less work had been done despite Nelson suggesting several tests based on orthogonality conditions that the errors of the model satisfy under the null hypothesis.

3.2 GJR-GARCH

The Glosten, Jagannathan and Runkle GARCH (GJR-GARCH), or just GJR, model, proposed by Glosten et al. (1993) allows the conditional variance to respond differently to the past negative and positive innovations. The GJR-GARCH similarly to the EGARCH belongs to the family of asymmetric GARCH models. The GJR formulation, closely related to the Threshold GARCH, or TGARCH, model proposed independently by Zakoian (1994) differs from the EGARCH in how it responds to negative volatility. Essentially, this model has an extra parameter to capture leverage in the data series. The parameter γ enters the model in such a way to enhance the volatility response to only adverse markets shocks. We can saythat $\varepsilon_t \sim GJR - GARCH$ is we can write $\varepsilon_t = \sigma_t z_t$, where z_t is standard Gaussian (for simplicity) and:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{[\varepsilon_{t-1<0}]} + \beta\sigma_{t-1}^2 \tag{7}$$

where > 0 , $\alpha \geq 0$, $\alpha + \gamma \geq 0$ and $\beta \geq 0$. $I_{\varepsilon_t<0} = 1$ if $\varepsilon_t < 0$ and 0 otherwise. $I(.)$ denotes the indicator function hence the model is sometimes referred to as a Sign-GARCH model.

When estimating the GJR model with equity index returns, γ is typically found to be positive, so that the volatility increases proportionally more following negative than positive shocks. Similar to the EGARCH, Bollerslev (2008) makes clear that the asymmetry is now widely agreed has little to do with actual financial leverage though referred to as a "leverage effect" in the literature.

In the GJR-GARCH model, good news, $\varepsilon_{t-1} > 0$ and bad news, $\varepsilon_{t-1} < 0$, have differential effects on the conditional variance; good news has an impact of α while bad news has an impact of $\alpha + \gamma$. If $\gamma > 0$, bad news increases volatility, and there is a leverage effect for for the ith order in α_{t-1}. If $\gamma \neq 0$, the news impact is asymmetric (Glosten et al., 1993). The news impact is captured by:

$$h_t = A + \alpha\varepsilon_{t-1}^2, \tag{8}$$

for $\varepsilon_{t-1} > 0$, and:

$$h_t = A + (\alpha + \gamma)\varepsilon_{t-1}^2, \tag{9}$$

for $\varepsilon_{t-1} < 0$,

where:

$$A \equiv \omega + \beta\sigma^2, \tag{10}$$

and σ is the unconditional standard deviation and ω is the constant term.

Engle & Ng (1993) postulated that the news impact curves capture the asymmetry in the distribution of the data in the way the two sides of the curve differ in slope to the left and right side of the vertical through $\varepsilon_{t-1} = 0$. Both models will assume a conditional skewed t-distribution to correctly mirror the fat-tails which characterise the distribution of the returns data.

We have elected to limit the model orders to (1,1) in the spirit of the literature. Brook & Burke (2003) amongst others indicate that the lag order (1,1) of GARCH models is sufficient to capture all of the volatility clustering that is present from the data.

3.3 Estimation of Parameters

The parameters of the family of GARCH models are estimated using the maximum likelihood method. The specific log-likelihood function is computed from the product of all conditional densities based on the assumption (s) prediction errors. Nelson (1991) discussed maximum likelihood estimation under the assumption that the errors have a generalized error distribution.

For the GJR-GARCH(1,1) model all the parameters $(\mu, \omega, \alpha, \gamma, \beta)$ are estimated simultaneously, by maximizing the log likelihood. The assumption that z_t is Gaussian does not imply the returns are Gaussian. Even though their conditional distribution is Gaussian, it can be proved that their unconditional distribution presents excess kurtosis (fat tails). In fact, assuming that the conditional distribution is Gaussian is not as restrictive as it seems: even if the true distribution is different, the so-called Quasi-Maximum Likelihood (QML) estimator is still consistent, under fairly mild regularity conditions (Bollerslev, 2008).

With similar assumption of z_t for EGARCH(1,1) the parameters of EGARCH (1,1) may be estimated by maximum likelihood. Under sufficient regularity conditions, the maximum likelihood estimators can be expected to be consistent and asymptotically normal (Malmsten, 2004).

4. Data and Results

The data comes from the Johannesburg Stock Exchange All Share Index spanning the years 2003 to 2015 giving us 3251 data points. A time series plot in Figure 1 shows there is a trend in the data.

We calculated the log-returns and plotted the time series to ascertain whether there are any regime changes (Hamilton, 1989; Ang & Timmermann, 2012). Assoe (1998) attributed such regime-switching in behaviour to changes in government policies and capital market reforms which often characterize developments in emerging markets.

Statistically these regimes are characterized by different data generating processes (see Assoe, 1998; van Norden & Schaller, 1993) with different statistical parameters. To detect the change points in the return series, we used the *changepoint* package of R Killick & Eckley (2010) and choosing the binary segment option proposed by Edwards & Cavalli-Sforza (1965), analysis led to the plot shown in Figure 3.

The plot in Figure 2 clearly shows multiple regimes - a period from 2003 to 2009, 2009 to 2010 and 2010 and beyond. The first two periods are characterised by a very volatile regime compared with the third period in which volatility seemed subdued.

The years 2003 to the end of 2009 exhibit a turbulent history. By contrast the years following that saw a moderation on the volatility with a brief not too severe breakout towards the end of 2012. To make it easier to model the data that is more reflective of the much recent volatility experienced in the market, we modelled the sub-period starting from January 2010 to December 2015. We show the time series of this period in Figure 4.

Figure 1: Time series of JSE ASI from 2003 to 2015

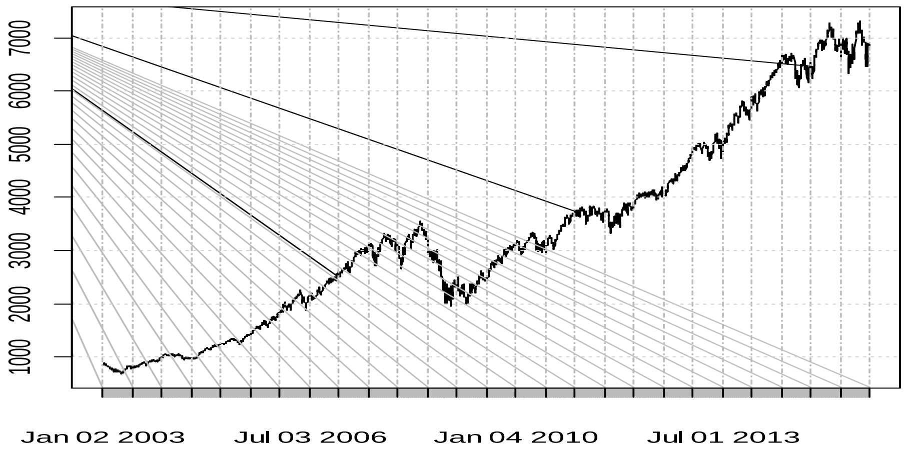


Figure 2: Time series plot of JSE ASI returns 2003 – 2015

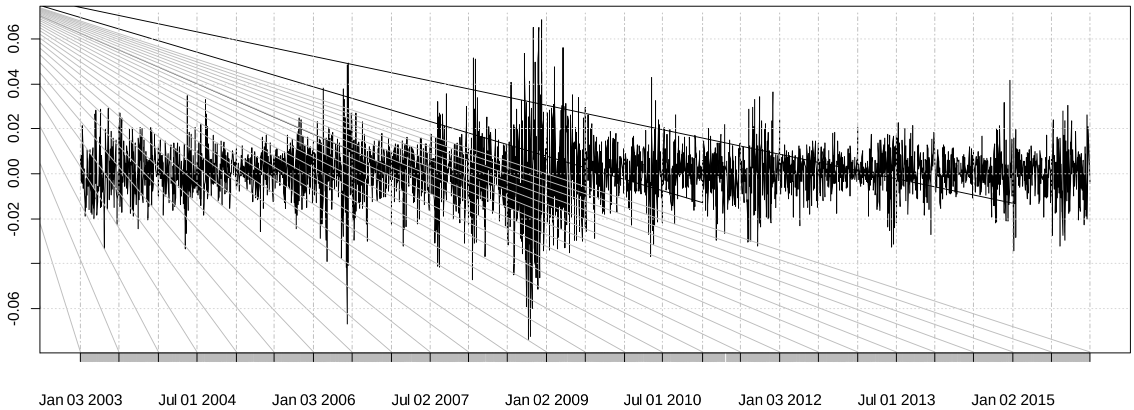


Figure 3: change points in the JSE returns data

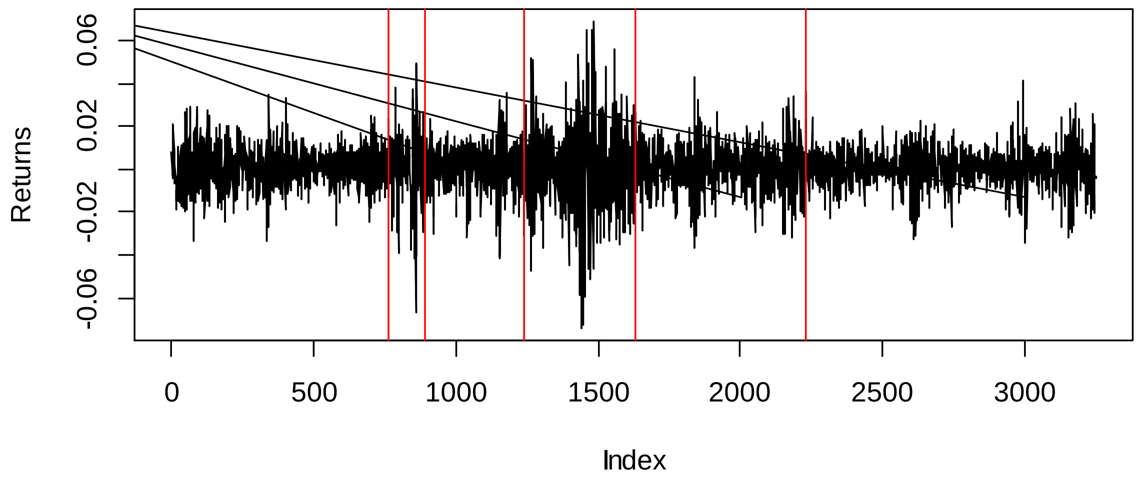
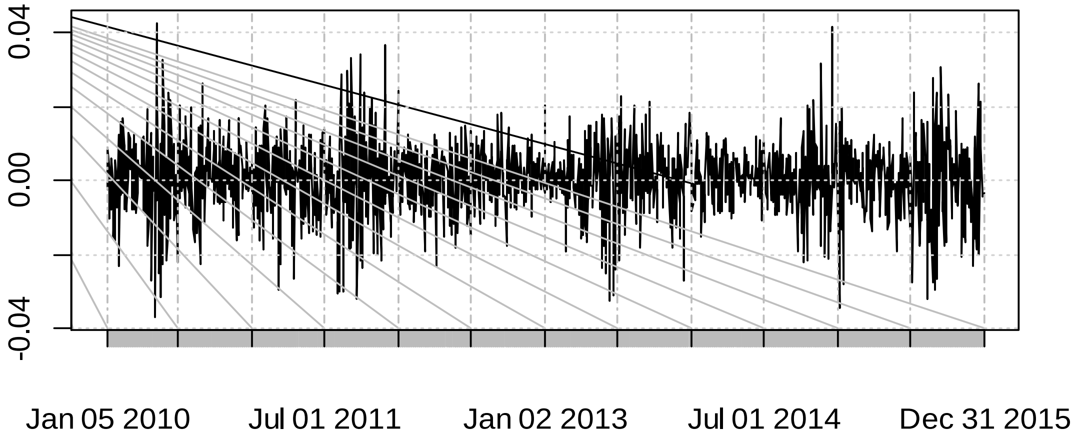


Figure 4: Time series plot of JSE returns 2010 – 2015



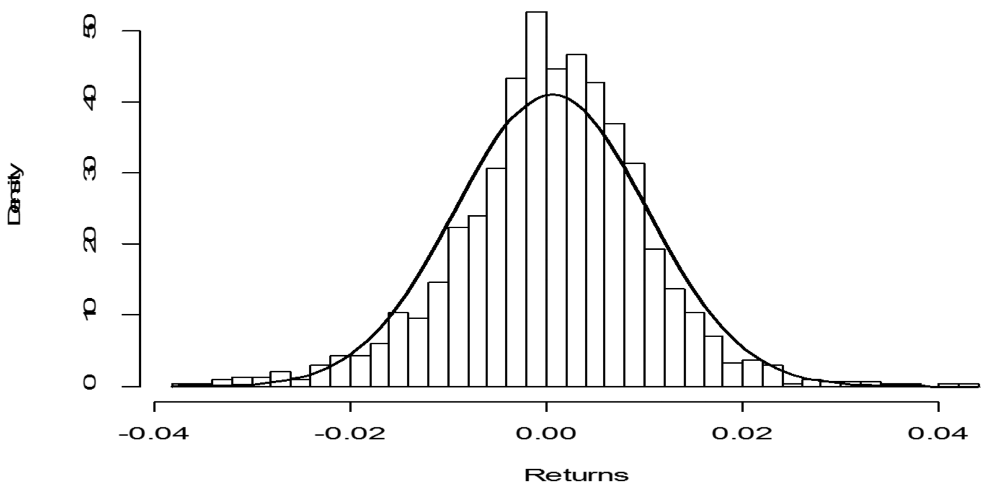
Formal tests using the Augmented Dickey-Fuller test yielded -11.719 ($p = 0.01$) thus rejecting the null hypothesis of non-stationarity in the returns series. The KPSS test also gave a level of 0.04841 ($p = 0.1$) thus failing to reject the null hypothesis of stationarity. A summary of the descriptive statistics of the returns is provided in Table 1.

Table 1: Summary statistics on JSE Returns 2010 – 2015

mean	Sd	skewness	Kurtosis
0.0005	0.0097	-0.1689	1.4196

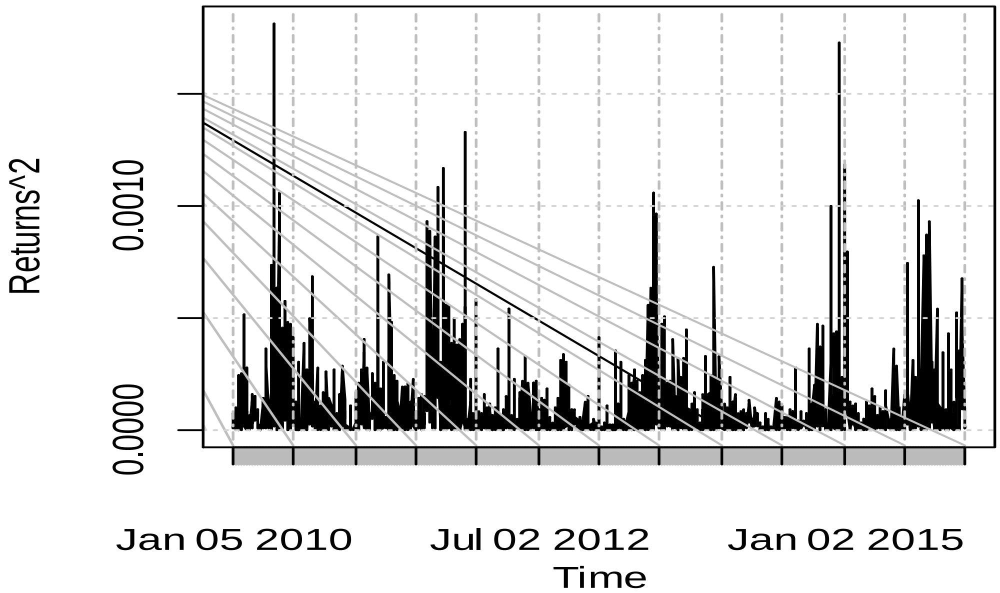
The data from the summary of statistics shows a slight skew to the left and fat-tails which characterizes market return data. Further test of Jarque-Bera and Shapiro-Wilk confirms the data shows departures from normality. A histogram of the market return in Figure 5 confirms the presence of the skewness and kurtosis to the left.

Figure 5: Histogram of the JSE returns 2010 – 2015



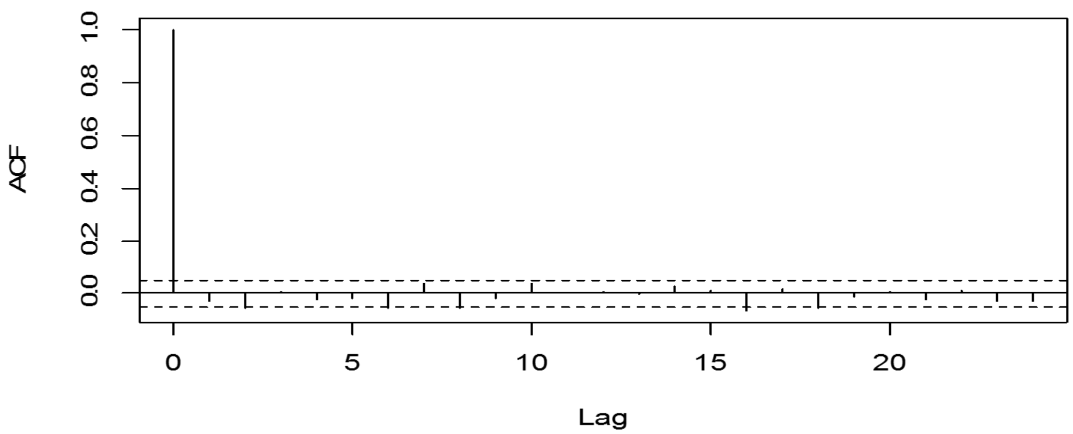
A further test for normality using the Jarque-Bera and Shapiro-Wilk normality tests yielded a chi-square of 133.6036 ($p < 0.5$) and Shapiro-Wilk statistic of 0.9834 ($p < 0.1$) (Royston, 1982). Both tests confirm nonnormality in the data. Stock markets are characterized by boombust cycles. Such cycles feed into the volatility of the markets. According to Campbell et al. (1997) bad news is received with extreme spikes in volatility than good news in the market. They also identified volatility clustering which is the tendency for volatility to be persistent for long period of time thus ruling out volatility jumps in asset prices. The JSE has been volatile throughout the period with persistent high volatility as the graph in Figure 6 shows. That is to be expected of an emerging or a developing market with a lot of changes and experimentation with policy in the underlying economy. Monetary and fiscal policies are transmitted to financial markets through interest rates. A period of low interest rates will see a surge in investments in the stock market and vice versa.

Figure 6: JSE squared returns 2010 – 2015



The autocorrelation function of the returns show in the graph (Figure 7) that some of the lags are significant confirming the presence of serial correlation in the return series.

Figure 7: Autocorrelation function of the JSE returns 2010 – 2015



A Ljung-Box test of the correlations gives a p-value of zero thus rejecting the null hypothesis of absence of serial correlation in the data. Thus we suspect the existence of ARCH effects in the series. To confirm the presence of ARCH effects, we used Engle's Langrange Multiplier test (Engle, 1982). A chi-squared value of 144.84 with 12 degrees of freedom gave a p-value which was less than 0.05 thus confirming the presence of ARCH effects in the returns series.

We modelled the JSE ASI return data using the EGARCH(1, 1) and GJR-GARCH(1,1) with the skewed student t-distribution to capture the behaviour in the tails of the volatility model. The summary of the results of parameters of both models are shown in Tables 2 and 3.

Table 2: Result of the EGARCH(1, 1) model

Parameter	**Estimate**	**Std. Error**	**t-value**	**p-value**
Omega	-0.43286	0.005277	-82.0224	0
alpha1	-0.16857	0.017626	-9.5633	0
beta1	0.954331	0.000121	7856.306	0
gamma1	0.080399	0.00907	8.8638	0
Shape	13.1212	3.641541	3.6032	0.000314

Table 3: Results of GJR-GARCH(1, 1) model

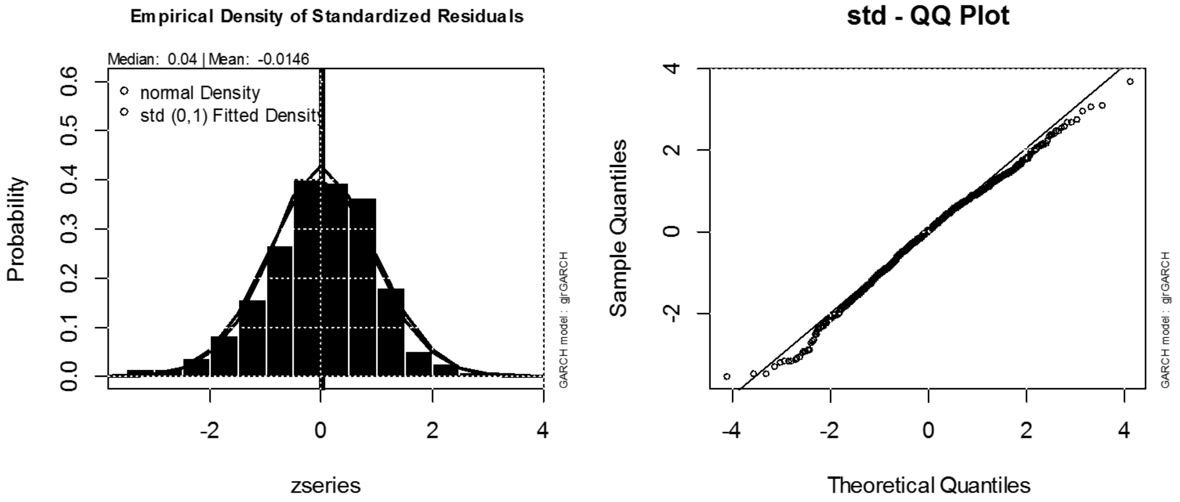
Parameter	**Estimate**	**Std. Error**	**t value**	**p-value**
Omega	0.000002	0.000009	0.22675	0.820619
alpha1	0	0.032602	0	1
beta1	0.908179	0.071333	12.73155	0
gamma1	0.13816	0.118218	1.16869	0.242529
Shape	12.52638	4.338334	2.88737	0.003885

The parameters in Tables 2 and 3 correspond to the definitions in the equations (1) and (7) for EGARCH(1,1) and GJR-GARC(1,1) the models respectively (i.e. $Omega = \omega, alpha1 = \alpha, beta1 = \beta, and\ gamma = \gamma$). The Shape is a logical flag which determines if the parameter for the shape of the conditional distribution will be estimated or not. The Shape parameters are estimated here; being significant at the 5% level justifies our use of the above asymmetric GARCH models.

The constraints on ω and α for the likelihood of the EGARCH(1,1) are violated; hence we discard the model.

A plot of the residuals from the GJR-GARCH(1,1) as shown in Figure 8 is reasonable in the assumption of the residuals being normal. The 'kick' in the lower tail of the residuals we guess was the brief period in 2012 when the market was particularly volatile.

Figure 8: Plot of residuals from GJR-GARCH(1, 1) model



We performed a historical backtest of the model GJR-GARCH(1, 1) to check its performance. We used Kupiec's unconditional coverage test Kupiec (1995) specifying a Value-at-Risk (VaR) exceedance of 0.01 and at confidence level of 0.99. We expect VaR exceedance should occur in only 1% of the cases. Using a hybrid solver and a moving window of 500 with a refitting of 25, with an expected exceedance of 5, we had actual exceedances to be 6. We had a p-value = 0.663 which is greater than the 0.05 significant level. We thus failed to reject the null hypothesis of actual exceedances are greater than the expected exceedances and conclude our model is adequate. Figure 9 and Figure 10 are plots of the actual versus expected returns and the backtesting performance of our model respectively.

Figure 9: Actual returns versus expected returns at VaR = 0.01

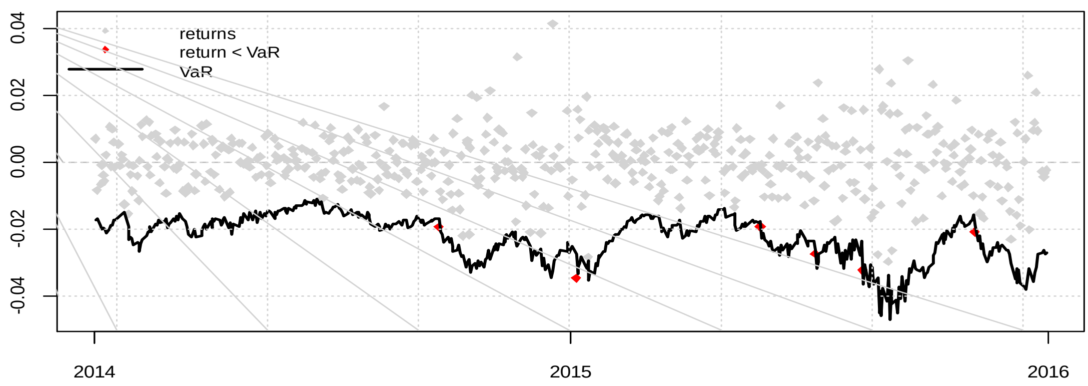
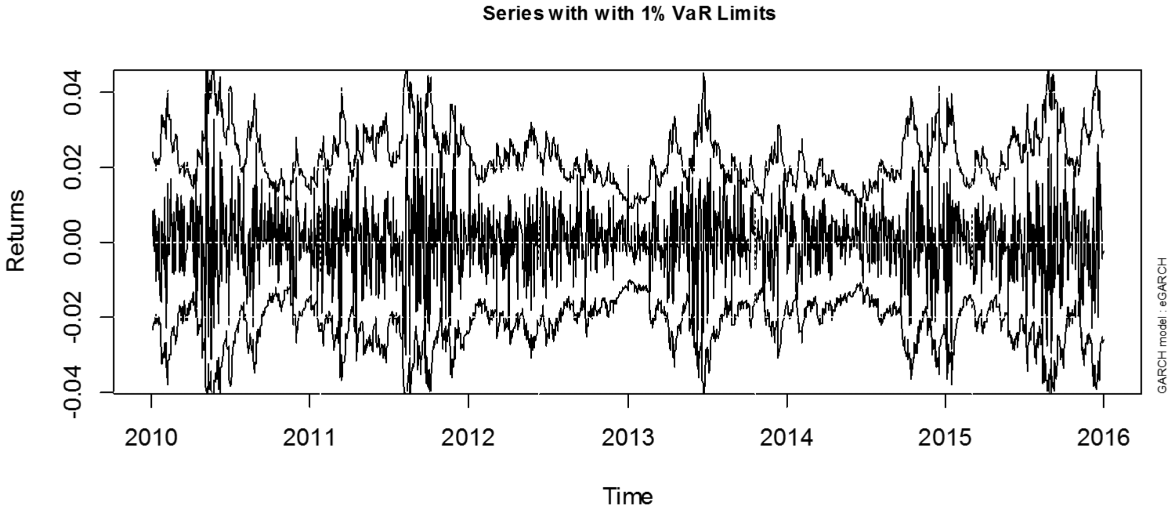
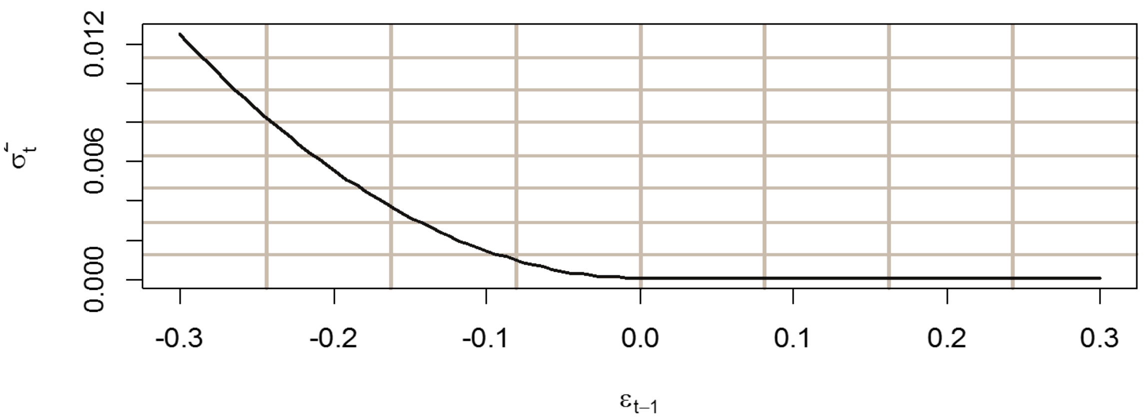


Figure 10: Performance of GJR-GARCH(1, 1) model from backtest



There is evidence that news, particularly 'bad' news has an inordinate influence on the returns on the market. The JSE reacts sharply to bad news and other adverse market related event as shown in Figure 11.

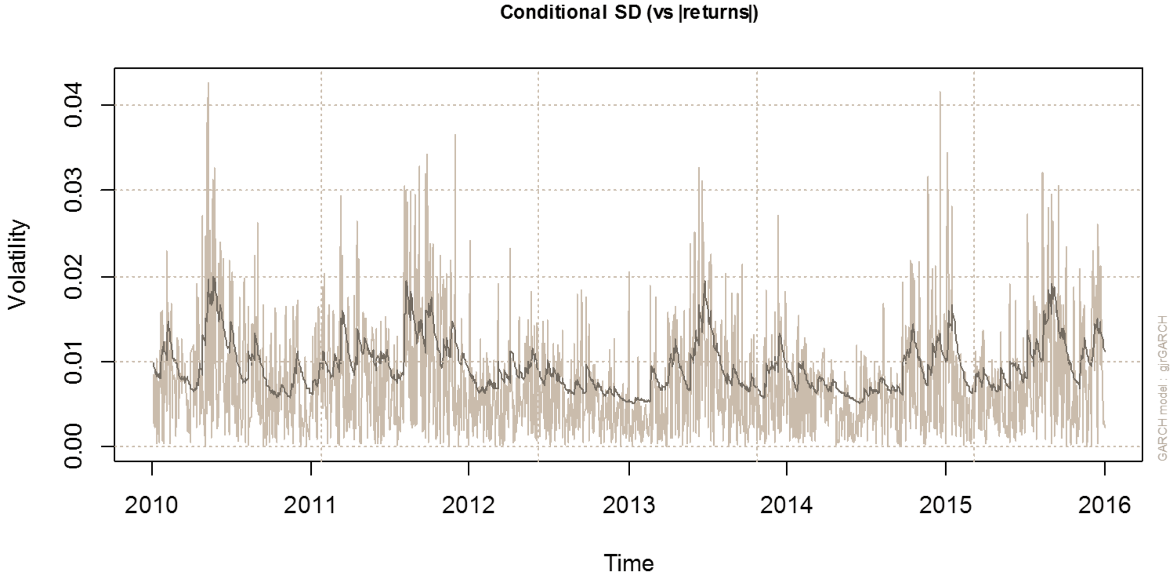
Figure 11: News impact curve of the GJR-GARCH(1, 1) model



As the diagram show in Figure 11, the markets is relatively unresponsive to good news compared to the surge in and sensitivity to volatility that accompanies bad news with sharp declines in prices of equities. What is not clear in the data is the source(s) of dominant news - company news, revisions to financial statements, regulatory action, and economic releases - eliciting this reaction from the investors. Investors tend to shrug off mild shocks. But beyond that it will appear there is a scramble for the exits as the diagram shows.

The alpha is zero compared to the beta. Thus the reaction of the conditional volatility to market shocks is relatively subdued. Ultimately the alpha is a measure of the sensitivity of the market to news. It is clear such a market has a relatively short memory. We would guess that news filter through developing and frontier markets swiftly and any corrections take place immediately. The beta confirms our observation in Figure 12 of the persistence of conditional volatility irrespective of what is happening in the market. Alexander (2008) postulates that a beta of 0.9 and above indicates that volatility will take a long time to die out following a market crisis. The graph in Figure 12 show the time plots of the evolving volatility of the returns of the JSE All Share Index.

Figure 12: Time plot of GJR-GARCH(1, 1) model



We predicted the one-year ahead volatility starting January 2016 (Figure 12). It is seen that as with any forecasting, the uncertainty increases with the increase in the forecast horizon. It is reasonable to assume the GJR-GARCH(1,1) together with the news impact reflects how volatility evolves and the market deals with adverse news reaching the market. Overall we have seen conditional volatility remaining elevated above the long term unconditional volatility for the forecasting period. Investor trading strategies have to take this into account as they shape their portfolios.

5. Conclusion

We have applied asymmetrical GARCH models to investigate the behaviour of the returns of the JSE All Share Index. We used the EGARCH(1,1) and GJR-GARCH(1,1) with skewed student-t distribution to capture tail behaviour. This selection was supported by preliminary analysis which showed departures from normality with some skewed and fat-tails. The constraints on omega and alpha for the EGARCH(1,1) were violated. Thus we adopted the GJR-GARCH(1,1) as the guiding conditional volatility model for the period from January 2010 to December 2015. We backtested our model and found it to be adequate in describing the adopted model. Unlike Chinzara (2011), this paper did not look at the influences exerted by the macroeconomic environment per se on the stock market. Taken on its own, we were looking at how investors can adapt their portfolios in an evolving risk environment in the presence of unexpected news. We believe our work as far as we know is the first one that incorporates explicit news impact into the analysis of time-varying volatility of returns from the Johannesburg Stock Exchange.

In information starved equity markets of the emerging markets, investors can be caught unawares by market moving news. As we have shown, market reaction to positive news has little to no effect on market volatility. Of concern to investors are the sharp reactions to negative news that characterise the data. We are guessing that the market will attract uninformed traders at this stage in its development. Such traders are most likely generating what will seem as the elevated reaction to news as they try to cut their losses at the first sign of trouble. Veronesi (1999) and DeLong et al. (1988) indeed document such phenomenon extensively in their studies. Investors may have to hedge against such "noise" in the market as it can erode any previous gains.

The market within the period has shown persistence in evolving volatility with the period. The level of forecasted volatility has been over all elevated but stable. Forecasting volatility, one of the unobserved market parameters, is challenging. However it is shown in statistics that $E(a_{h+1}^2|F_h) = \sigma_{h+1}^2$ so that a_{h+1}^2 is a consistent estimate of σ_{h+1}^2 (Andersen & Bollerslev, 1998; Francq & Zakoïan 2010). Overall investors in the South African equity market should be circumspect of the returns of the market given the asymmetry of the returns and their distribution.

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