RHODES UNIVERSITY
Where leaders learn

Risk-return tradeoff and the behaviour of volatility on the South African stock market: Evidence from both aggregate and disaggregate data

Mandimika, N.Z. and Chinzara, Z.

Working Paper 198

November 2010

Risk-return tradeoff and the behaviour of volatility on the South African Stock market: Evidence from both aggregate and disaggregate data*

Mandimika, N.Z.♠ and Chinzara, Z.♣

Abstract

The study analyses the nature and behaviour of volatility, the risk-return relationship and the long-term trend of volatility on the South African equity markets, using aggregate-level, industrial-level and sectoral-level daily data for the period 1995-2009. By employing dummy variables for the Asian and the sub-prime financial crises and the 11 September political shock, the study further examines whether the long-term trend of volatility structurally breaks during financial crises and major political shocks. Three time-varying GARCH models were employed: one of them symmetric, and the other two asymmetric. Each of these models was estimated based on three error distributional assumptions. The findings of the study are as follows: Firstly, volatility is largely persistent and asymmetric. Secondly, risk at both the aggregate and disaggregate level is generally not a priced factor on the South African stock market. Thirdly, the TARCH-M model under the Generalised Error Distribution is the most appropriate model for conditional volatility of the South African stock market. Fourthly, volatility generally increases over time and its trend structurally breaks during financial crises and major global shocks. The policy and investment implications of the findings are outlined.

Keywords: Risk-return tradeoff, stock market volatility, asymmetric GARCH models
JEL Classification: G10, G11, G12, C52

1. Introduction

Since Markowitz (1952) settled on the idea that investors would demand higher returns on a market portfolio than a risk-free investment, the relationship between risk and return has been subjected to extensive theoretical and empirical enquiry. This comes as no surprise given the importance of risk in the pricing of financial assets and financial derivatives, and in portfolio diversification. In a major theoretical breakthrough, Merton (1973) demonstrated that, subject to risk-averseness, conditional expected excess returns on the aggregate market are a positive function of their conditional variance. Denoting an indirect utility function by *J (.)*, aggregate wealth by W_t, conditional expected returns on aggregate wealth between time t and $t+1$ by ε_{wt+1}, and conditional variance of returns on aggregate wealth by ($\sigma^2_{W_{t+1}}$), Merton (1973) showed that, under the assumption of a fixed investment opportunity set or of

* The Financial support from ERSA is acknowledged. Views and opinions expressed are of the authors and do not necessarily represent those of ERSA.
♠Department of Economics, Rhodes University, P.O. Box 94 Grahamstown 6140. Email: nzmandimika@yahoo.com.
♣ Correspondence Author. Department of Economics, Rhodes University, Email: zchinzara@yahoo.com.

Gaussian distribution of rate of returns, the relationship between return and risk can be described by the following function:

$$\left(\varepsilon_{W_{t+1}}\right) = \left[\frac{-J_{WW}W_t}{J_W}\right]\left(\sigma^2_{W_{t+1}}\right) = \lambda(\sigma^2_{W_{t+1}}) \quad (1)$$

where $[-J_{WW}W_t/J_W]$ is a measure of risk averseness of investors that can be denoted by λ. Equation (1) shows that the returns that investors expect to earn in the future are directly proportional to the product of the expected variation in returns and a measure of risk averseness . Because investors are generally risk-averse, they will invest in a project if the expected returns from such an investment are high enough to compensate for the expected riskiness of that investment, thus λ is expected to exhibit a positive sign.

Over the past three decades, several empirical studies based on different methodologies have tested the existence of risk-premia in returns of developed, emerging and developing stock markets, albeit with mixed results. For developed stock markets, Campbell (1985) and Harvey (1991) used the instrumental-variable technique to document a positive risk-return relationship for the US and a negative risk-return relationship for the 16 OECD countries. Using a two-stage Markov Switching model, Turner *et al*. (1989) found that the relationship between risk and return is not stable but changes from positive to negative from time to time. French *et al*. (1987), Chou (1988), Glosten *et al*. (1993), Theodossiou and Lee (1995), Hansson and Hordahl (1998), Jochum (1999), and Lanne and Saikkonen (2004) used different specifications of univariate (some authors) and multivariate (other authors) Generalised Autoregressive Conditional Heteroskedastic-in-mean (GARCH-M) family of models to document mixed evidence about the existence of the risk-premia in the developed stock markets of the US, Europe, Australia and Asia. Thomas and Wickens (1989) and Pagan and Hong (1991) used non-parametric models to find weak evidence of a positive risk-premium for German, Japan, UK and weak evidence of a negative risk-premium for the US respectively.[1]

For emerging markets, Poshakwale and Murinde (2001) used the GARCH-M model to show that risk was not a priced factor for the Eastern Europe emerging market. Using the EGARCH-M model, Karmakar (2007) and Saleem (2007) found significant evidence of a positive risk-premium for India and Pakistan respectively. Using the same model, Yu and Hassan (2008) studied the Middle East and North Africa (MENA) region and found significant positive risk-premia for Bahrain, Oman and Saudi Arabia, and significant negative risk-premia for Egypt, Jordan, Morocco and Turkey. Kovačić (2008) and Leon (2008) used different GARCH-type models under different error distributions to document weak evidence of positive risk-premia for Macedonia and for the West African Economic and Monetary Union countries respectively.

Despite the fact that the South African stock market is the largest and most liquid market in Africa, studies on the risk-return relationship have remained limited until recently. The only relevant study for South Africa is by Mangani (2008) who studied the risk-return relationship using weekly data on 42 individual stocks and two portfolios, the first based on the ALSI and the second composed of equally weighted portfolios of the 42 stocks. Using the

[1] The studies are not reviewed individually for succinctness. However their results vary from country to country.

GARCH-type models, Mangani (2008) found that, expect for two stocks, volatility is largely an unpriced factor. Furthermore, the author found limited evidence of leverage effects and asymmetry in volatility for the portfolios and most of the stocks.

The current study is in the same spirit as Mangani (2008), but tries to address some of the shortfalls of the latter. Firstly, unlike in Mangani (2008), daily data comprised of the four benchmark indices for the aggregate market, nine industrial indices and 33 sectoral indices are used. Since a number of studies document that the South African stock market is informationally efficient (see Mkhize and Msweli-Mbanga, 2006:85), higher frequency (daily) data will provide better dynamics of the return-generating process than lower-frequency (weekly) data. Secondly, the finding of limited evidence of asymmetry by Mangani (2008) is questionable as it contrasts a number of studies that show that stock market data are characterised by volatility asymmetry (cf. Karmakar, 2007, Leon *et al.*, 2005, and Koutmos, 1996). In fact, more recent studies by Chinzara and Aziakpono (2009) and Chinzara (2010) document that volatilities of the aggregate and four main sectors of the South African stock market are inherently asymmetric. A possible explanation of the difference in conclusions pertaining to the symmetry of volatility could be due to the fact the two latter studies used more recent data (1995-2008) than Mangani (2008), who used data from 1973-2002. Thirdly, while the majority of relevant studies use GARCH models,[2] most of those studies assume the Gaussian distribution of returns in estimating their models. Koop (1994) argues that models that assume normal distribution of the error term are likely to face the risk of misspecification. In this regard and in line with Kovačić (2008) and Leon (2008), the current study assumes three error distributions[3] and then compares the estimated results from the three distributions to determine the most appropriate one. Finally, the current study also analyses the long-term behaviour of volatility at both aggregate and sectoral level, and further investigates whether the long-term trend of volatility is subject to structural breaks during major world shocks and financial crises.

The remainder of the paper is structured as follows: Section 2 describes the data used and discusses some of properties of the data. Section 3 presents the methodologies used to analyse the behaviour of volatility, the risk-return relationship and the long-term trend in volatility. Section 4 reports and discusses the results of the study. Section 5 sums up the paper, and articulates the policy implications as well as suggesting further areas for research.

2. Data and Descriptive Statistics

Data used comprise daily indices for four JSE benchmark indices, nine industrial indices, and 33 sectoral indices (including two subsectors) of South Africa’s equity markets, as defined by the Industry Classification Benchmark (ICB) for the period 30/06/1995 to 31/07/2009, totalling 46 indices and 3 677 observations per index, and was obtained from Thompson Datastream.[4] The choice of the industries, sectors and subsectors, as well as the period of study was based primarily on data availability. Non-trading days (e.g. holidays and

[2] GARCH models have been widely commended for their ability to model time-varying volatility.

[3] Gaussian, Generalised Error distribution and Student–*t* distribution

[4] Note that a few indices started after 2000, so their data are not available from 1995.

weekends) and thin trading raise concerns regarding the relevance of using daily data. However, the speed at which stock prices assimilate new information make daily data an attractive choice – particularly given their ability to capture daily trading information dynamics. In line with Chowdhury (1994), Chang *et al*. (2006) and Chinzara and Aziakpono (2009), all the non-traded days were removed from the data.

As a practice in standard empirical literature, the daily index series were converted into continuous compounded returns as follows:

$$y_t = (\ln P_t - \ln P_{t-1}) * 100 \quad (2)$$

where y_t denotes the continuous compounded returns at time t, P_t is the closing stock price index at time t and P_{t-1} is the closing stock price index for the previous day. Equation (2) has the advantage of removing the need to consider explicitly the rate at which the returns are compounded. Table 1 provides the general properties of the returns, particularly on descriptive statistics, stationarity, serial correlation, and heteroscedasticity tests.

The reported descriptive statistics are sample means, median, maximum, minimum, standard deviation, skewness, kurtosis and the Jarque-Bera statistics. With the exception of Forestry and Paper, Automobile and Parts, Household Goods and the AltX, all mean returns are positive, implying a bullish market over the sample period. Risk, as measured by standard deviation of returns, is highest in the Consumer Goods industry, ranging from 0.548%-1.372%, while the Industrials industry is the least volatile, ranging from 0.566%-0.675%. If risk is a commonly priced factor we would expect the highest mean returns to be matched by the highest standard deviation. However, from the descriptive statistics this relationship is not apparent. It is evident that the highest mean returns are in the Pharmaceuticals and Biotechnology sector (0.034%) while the lowest are in the Automobile and Parts sector (-0.02%); however the highest standard deviation is found in the Automobile and Parts sector (1.372), while the lowest standard deviation is found in the Real Estate sector (0.444).[5] From this casual observation there is no discernable positive relationship between risk and return. In fact, it seems that the Automobile and Parts sector exhibits a negative risk-return relationship.

Generally the data exhibit characteristics that are common with financial series. For instance, the highly statistically significant Jarque-Bera test statistics imply that the distribution of the returns departs from normality. More clearly, the non-normality of the data is confirmed by the skewness and the kurtosis parameters. Of the 53, 39 are negatively skewed while 14 are positively skewed. The fact that the majority of the returns are negatively skewed, implies that the return distributions of the sectors and indices have a probability of earning returns greater than the mean (Karmakar 2007:101).The high kurtosis ratios imply that the distribution of the returns are characterised by fat tails. Both the Augmented Dickey Fuller (ADF) and the KPSS statistics show that all the returns series are stationary.[6]

[5] Although the Small and Mid Cap series have the lowest standard deviation, the Real Estate sector has the lowest standard deviation amongst all the Industries and Sectors.

[6] The KPSS was used as a confirmatory test since the ADF test may be biased towards rejection of the null hypothesis in cases where the error terms follow an MA or ARMA process (see Davidson & MacKinnon,

Ljung-Box statistics for both returns [LB(12)] and squared returns [$LB^2(12)$] are statistically significant. The former implies the existence of serial correlation in returns, a contrast to the informational efficiency of the stock market. Methodologically, this justifies the need for an autoregressive component in the mean equation to *whiten* the error term. The latter case entails that there is evidence of volatility clustering and heteroscedasticity (i.e. time-varying second moments), thus justifying the use of the GARCH family of models, as they capture the time-varying nature of conditional volatility (Kovačić, 2008:193; Magnus and Fosu, 2006:2044).[7]

3. Methodology

This study is divided into two parts. The first part analyses properties of volatility and the risk-return relationship. The second part involves estimating conditional volatility and analysing its behaviour over time and whether volatility structurally breaks during sudden global political events and financial crises. To examine the relationship between daily returns and conditional risk, one symmetrical and two asymmetrical univariate GARCH-in-mean models were employed. The models were then estimated under three distributional assumptions. While there is literature that might suggest the superiority of some types of models over others, or of some distributional assumptions over others (see Brooks, 2002), experimentation seems to suggest that the performance of different models under different distribution assumptions may depend on the underlying properties of the data. In light of this, the idea here is to compare the performance of three GARCH-in-mean models across the three distributional assumptions, and also to examine whether the risk-return relationship varies depending on model specification.

Proposed by Engle, Lilien and Robins (1987), the ARCH-M specifies the mean returns of a security as a linear function of time-varying conditional risk/variance. In the original ARCH-M model, the time-varying conditional variance is specified as a function of squared past error terms from the mean equation. However, given the superiority of GARCH models over the original ARCH model (see Tse, 1998; Brooks, 2002), in this study the conditional variance is modelled using the symmetric and two asymmetric GARCH models.

More generally, a GARCH-M (p, q) model is specified as follows:

$$r_t = \mu_i + \sum_{i=1}^{k} a_i r_{t-i} + \delta_i \sqrt{h_{t-i}} + \varepsilon_t \qquad , \varepsilon_t / I_{t-1} \sim N(0, h_t^2) \tag{3a}$$

2004:622). The appropriate lag for the ADF equation was determined using the Schwarz information criterion with maximum lag set at 30 days. Given that stationarity tests are just an intermediate step and that both the KPSS and ADF are widely documented in textbooks and empirical literature, the theoretical technicalities of these tests will not be discussed here. For discussion see e.g. Brooks (2002) and Gujarati (2009).

[7] Visual inspection of returns series also showed that their variances change over time, with small (large) changes tending to be followed by small (large) changes. This reinforces the appropriateness of GARCH models. Given that there are up to 46 returns series, it will be impractical to report the graphs here. However, they are available on request.

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \text{ , } \omega > 0, \quad |\alpha_i + \beta_j| < 1 \qquad (3b)$$

where Equation (3a) is an appropriate mean equation whose current error term ε_t, given the previous day's information set I_{t-1}, has a mean of *zero*, a variance of h_t, and is serially uncorrelated[8]; r_t and r_{t-i} denote the current and lagged returns respectively, and $\sqrt{h_{t-i}}$ is the conditional standard error of ε_t at time *t-i*. Equation (3b) is a GARCH (p, q) variance equation, where h_t is the conditional variance of the residuals (ε_t), ω is a constant, α_i is the coefficient of the lagged squared residuals that are generated from the mean equation (i.e. ε^2_{t-i}), and β_j is the coefficient for the lagged conditional variance (h_{t-j}). Because the GARCH (p, q) assumes that the condition that $\omega>0$, $\alpha_i>0;\beta_j>0$ is satisfied, h_t is always positive. The condition given in (3b), i.e. $|\alpha_i + \beta_j| < 1$, is necessary for the stationarity of the GARCH model, otherwise the variance will be unstable and shocks will be explosive (Brooks, 2002).

Particularly important with respect to this study is the coefficient of $\sqrt{h_{t-i}}$. This coefficient (δ_i) shows the link between returns (r_t) and conditional risk ($\sqrt{h_{t-i}}$). If δ_i is positive and statistically significant, then in accordance with the portfolio theory, investors are rewarded with higher returns for their higher risk appetite. More technically, this would imply that risk is a priced factor in the period under study.

Nevertheless, there are some drawbacks with the GARCH (p, q) variance specification. Firstly, the GARCH (p, q) in general and the GARCH (1, 1) in particular, may be weakly identified if α_i is too small.[9] This results in the understatement of standard errors and upwardly biased t-tests, and thus leads to a wrong inference that volatility is persistent even when it is not (Ma, *et al.,* 2007). Secondly, the GARCH (p, q) does not capture volatility asymmetry, which usually characterises stock markets. In this regard it could be necessary to extend it with an asymmetry component, thus the threshold GARCH (TARCH/GJR GARCH) model and the exponential GARCH (EGARCH) are also explored.[10]

Proposed by Zakoian (1990) and Glosten *et al*. (1993), GJR GARCH (p, q) takes the same mean equation as (3a) and simply re-specifies the GARCH (p, r, q) model with an additional term to account for asymmetry as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{m} \gamma_k \varepsilon_{t-k}^2 I_{t-k} + \sum_{j=1}^{q} \beta_j h_{t-j} \text{ ; } \omega > 0, \quad |\alpha_i + \beta_j| < 1 \qquad (4)$$

[8] The autoregressive (AR) lags of the return/growth series are added to *whiten* the error term. This is especially important given that the Ljung-Box statistics for all the series were statistically significant, implying the presence of autocorrelation in the series. Thus AR terms will be added until serial correlation is dealt with. The tests for autocorrelation are based on the Durbin-Watson (DW) and the Breusch-Godfrey LM (B-G) tests.

[9] This phenomenon is termed Zero-Information-Limit-Condition (ZILC). For an elaborate discussion of the (ZILC), see Nelson and Startz (2007) and for the implications of ZILC for the GARCH (1, 1) model see Ma, *et al.,* 2007

[10] Brooks (2002:469) among others suggests that equity returns exhibit asymmetric responses of volatility to positive and negative shocks. Asymmetric responses are attributed to leverage effects, which occur when a fall in the value of a firm's stock causes the firm's debt-to-equity ratio to rise, which leads ordinary shareholders to perceive their future cash flow stream as being relatively more risky.

where $I_{t-k} = 1$ *if* $\varepsilon_{t-k}<0$, *or* $= 0$ *if* $\varepsilon_{t-k}>0$, I_{t-k} is the asymmetry component and γ_k is the asymmetry coefficient. If the asymmetry coefficient is positive and significant (i.e. $\gamma_k > 0$), then this would imply the existence of leverage effects or asymmetry in volatility. Asymmetry in volatility is based on the intuition that good news ($\varepsilon_{t-k} >0$) and bad news ($\varepsilon_{t-k} <0$) have different impacts on conditional volatility, which can be depicted as α_i and $\alpha_i+\gamma_k$ respectively. If γ_k is statistically significant, then clearly the impact of good news on volatility is different from that of bad news. If $\gamma_k > 0$, the leverage effect exists in stock markets and if $\gamma_k \neq 0$ then the impact of news is asymmetric (Brooks, 2002).[11] The other coefficients α_i and β_j are interpreted as in the GARCH (p, q) model.

A possible weakness with both the GARCH (p, r,) and GJR GARCH (p, r, q) specifications of the variance is that the 'artificial' non-negativity assumptions that are made about parameters α_i and β_j may be violated in real analysis of financial data. Thus the EGARCH model may be necessary since its logarithmic functional form ensures that the conditional variance will always be positive irrespective of the sign of the parameter. Proposed by Nelson (1991), the EGARCH (p, m, q) model also adopts a mean equation like (3a), but specifies the variance equation as follows:

$$\log(h_t) = \omega + \sum_{j=1}^{p} \beta_j \log h_{t-j} + \sum_{k=1}^{m} \gamma_k \frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} + \sum_{i=1}^{q} \alpha_i \left[\left| \frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} - E\left(\frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right) \right| \right]; \qquad (5)$$

$$\omega > 0, \quad \left| \alpha_i + \beta_j \right| < 1; \gamma_k < 0, \textit{ if volatility is asymmetric.}$$

where α_i and β_j are still interpreted as they are in the GARCH (p, q) model. As in the GJR GARCH model, γ_k is the asymmetry coefficient, although its interpretation differs. If $\gamma_k < 0$ and significant, then volatility is asymmetric (Brooks, 2002:469).

In order to estimate the above models, it is necessary to make assumptions about the distribution of the error term. Although Table 1 shows that the returns series departs from normality, the log-likelihood function for the GARCH models does not necessarily require the series to be normally distributed. Following Kovačić (2008) and Leon (2008), three error distributional assumptions are explored for each of the three models: *the Gaussian distribution, the Student–t distribution and the Generalised Error Distribution (GED)*. The log-likelihood function under the Gaussian distribution is specified as follows:

$$l_t = -\frac{1}{2} log(2\pi) - \frac{1}{2} log\sigma_t^2 - \frac{1}{2}(r_t - \theta r_{t-1})^2/\sigma_t^2, \qquad (6)$$

where r_t and r_{t-1} denote current and lagged returns respectively, $0<\theta<1$, t is the number of the observations and other variables are as defined earlier.

[11] The difference between $\gamma_k > 0$ and $\gamma_k \neq 0$ is that the former case would imply that there is evidence for both leverage and asymmetric effects. In the latter case γ_k can take both positive and negative values. Should it take a negative value, then only evidence of asymmetric effects and not leverage effects exist in the data (Eviews 6 Manual, 2009).

A common feature of financial data is that they are characterised by fat tails. The Student–*t* distribution and the GED are normally used to account for this phenomenon. Under the Student–*t* distribution, the log-likelihood function takes the following form:

$$l_t = -\frac{1}{2}log\left(\frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma((v+1)/2)^2}\right) - \frac{1}{2}log\sigma_t^2 - \frac{(v+1)}{2}\log\left(1+\frac{(r_t-\theta r_{t-1})^2}{\sigma_t^2(v-2)}\right) \quad (7)$$

given $\Gamma(\cdot)$ is the gamma function and $v>2$ is the shape parameter which controls for the tail behaviour. It should be noted that as $v \rightarrow \infty$ the Student–*t* distribution converges to the normal distribution.

Proposed by Nelson (1991), the log likelihood under the GED is as follows:

$$l_t = -\frac{1}{2}log\left(\frac{\Gamma(1/v)^3}{\Gamma(3/v)(v/2)^2}\right) - -\frac{1}{2}log\sigma_t^2 - \left(\frac{\Gamma(3/v)(r_t-\theta r_{t-1})^2}{\sigma_t^2\Gamma(1/v)}\right)^{v/2} \quad (8)$$

where $\Gamma(\cdot)$ is defined as in Equation (7), v is a positive parameter (i.e. $v > 0$) that describes thickness of the tails. The GED is a normal distribution if $v=2$, and fat-tailed if $r<2$.[12]

The parameters for the models were estimated using the Maximum Likelihood (ML) approach, which involved applying the Marquardt algorithm to the above log-likelihood functions. The ML approach requires that initial parameters are specified. Eviews estimation software provides its own initial parameters for the ARCH procedures based on the mean equation (Eviews 5, 2007:192), which could then be altered manually if convergence is not achieved or if parameter estimates are implausible (Brooks, 2002). Neither of the two problems were encountered, thus the authors utilised the initial values provided by Eviews in all the estimations.[13] Diagnostic tests for heteroscedasticity and autocorrelation based on the Arch LM test and the Box-Pierce-Ljung statistic were done for all the estimated models.

Once the models were estimated, the next step involved comparing the performance of the models under the different error distributions to select the most appropriate model for each of the series. The comparison was based on whether there was significant evidence of asymmetry in the data, whether the model was stationary ($|\alpha_i + \beta_i| < 1$), and whether the model had good diagnostic properties. In cases where the performance of the models was indistinguishable in the above aspects, the model with the lowest Schwarz (1978) Bayesian Information Criteria (SIC) was considered as the most appropriate.[14] Using the most appropriate model, the time-varying conditional variance of each of the returns (a proxy for returns volatility) series was then estimated.

Given that stock market volatility is a source of financial and macroeconomic instability (Chinzara and Aziakpono, 2009), it is important to analyse its trend over time. Excessive stock market volatility may affect/inhibit the smooth functioning of the other financial markets and subsequently negatively affect savings, investments, economic growth,

[12] For a detailed discussion on the distributional properties of the Student–*t* and GED distributions refer to Knight and Satchell (2001:153) and Zivot and Wang (2006:257).

[13] For robustness, alternative manually selected initial values were attempted, but results did not show any significant sensitivity. Thus, the reported coefficients for the respective GARCH models are robust.

[14] The SIC is used because it embodies a much stiffer penalty term than the Akaike (1978) Information Criterion (AIC) (Brooks, 2002:257).

and the performance of the real economy in two ways. Firstly, stock market volatility creates uncertainty in an economy, which usually results in capital flight. This complicates the task of macro-economic policy makers who are charged with creating an environment that fosters real economic growth by controlling policy variables such as interest rates, which are significantly influenced by capital flows (Rigobon and Sack, 2003). Secondly, because a rise in volatility in the equity markets is usually interpreted as a rise in equity-risk, this could subsequently cause a shift in investment funds to flow towards less risky assets. This move could increase the cost of funds for new firms as investors seek to invest in 'blue chip' companies (Edwards and Garcia, 2008:61). This flow of funds away from equity markets could make it difficult for both new and well-established firms to plan and budget accurately for long-term projects as the availability of investment funds from the stock markets becomes uncertain. The effect of these factors could adversely impact the performance of an economy at large. Therefore, it is imperative that policy makers have knowledge of stock market volatility over time.

On the one hand investors are interested in stock market volatility, as the central idea of investment in stock markets (and financial markets at large) is based on the ability to maximise return per unit of risk. Moreover, investors would be interested in the trends of volatility over time on the stock markets as this would inform their investment decisions such as portfolio diversification.

To analyse the trend of volatility, a benchmark approach by Frömmel and Menkhoff (2003) and Chinzara and Aziakpono (2009) was adopted but augmented by adding dummy variables for the 1997-1998 Asian crises, September 2001 political shock, and 2007-2009 sub-prime financial crisis to assess whether the trends structurally broke due to those shocks. The augmented model is as follows:

$$h_t^2 = \beta_1 + \beta_2 T + \beta_3 DUM1 + \beta_4 DUM2 + \beta_5 DUM3 + u_t \qquad (9)$$

where h_t^2 is the conditional variance for each of the returns series, and T is the time variable. The coefficient β_2 shows the general trend of volatility over the period of study. A positive (negative) and significant β_2 would mean that volatility significantly increased (decreased) over the sample period. *DUM1=1* if the period is the Asian crisis, 0 otherwise, *DUM2=1* if the period corresponds to the global shocks due to the 11 September attacks, 0 otherwise, and *DUM3 =1* if the period is the sub-prime financial crisis, 0 if otherwise.[15] If the coefficients of any of the dummy variables, β_3, β_4 or β_5, are positive and significant this would mean that there was a structural break in volatility during the period concerned.

4. Empirical Results

4.1 The Behaviour of Volatility

[15] The exact dates for the dummy variables are as follows: Asian Crisis: 1997/10/27 – 1998/12/21; September 11 shocks: 2001/09/11 – 2002/03/13; Sub-prime crisis: 01/01/2008 – 31/07/2009.

The starting point for all our estimations was to determine the appropriate mean equations for each of the return series. This involved estimating and testing the mean equation for serial correlation using the DW and the B-G tests. The results for the mean equations are reported in Table 2. As evident in most of the mean equations, serial correlation was dealt with after adding one autoregressive [i.e. AR(1)] lag, and in a few circumstances after adding two autoregressive lags [i.e. AR(2)]. The ARCH-in-mean models for each of the series were then estimated based on the appropriate mean equations. A total of 414 models were estimated and the results are reported in Table 3.

As evident in Table 3, most of the GARCH-in-mean were stationary [i.e. $\alpha+\beta<1$][16] except for those for the Industrial Metals (GED), Automobile and Parts (Student–*t* and GED), Personal Goods (Gaussian), Media (Student–*t*), Pharmaceuticals and Biotechnology (Student–*t*) and Industrial Engineering (Student–*t* and GED) which are non-stationary.[17] A similar result is also evident from the TARCH-in-mean model where explosive volatility is evidenced in only a few sectors. However, for most of the returns (across GARCH and TARCH specifications), $\alpha+\beta$ is very close to one, implying that the returns-generating processes are characterised by high degree of persistence or long memory in conditional variance. Therefore, any 'shock' in volatility in the current period will persist for many future periods (see Magnus and Fosu, 2046:2006). The EGARCH-in-mean model, on the other hand, is largely non-stationary and the results from this model show that a shock in returns will continue to grow indefinitely into the future.

The results show that there is significant evidence of asymmetry and leverage effects in all the returns except for Automobile and Parts and Real Estate (Gaussian) returns.[18] This implies that unexpected bad news increases volatility more than unexpected good news of similar magnitude. There are two common economic explanations for leverage effects. The first explanation hinges on the leverage effect hypothesis postulated by Black (1976) and Christie (1982). If the price of a share drops (negative return), financial leverage increases, leading to an increase in stock return volatility. These financial 'leverage effects' have become associated or synonymous with asymmetric volatility and yet it is possible that the evidence of asymmetric volatility could simply reflect the existence of time-varying risk-premia. The second explanation centres on the relationship between volatility and expected returns. In the event of an anticipated increase in volatility, expected returns tend to increase, leading to a decline in the stock price. This is because volatility is a measure of risk, and if investors are assumed to be risk-averse, an increase in risk (volatility) will result in a decline in demand for that stock, leading to a fall in price. If volatility is priced, then an increase in volatility raises the required return on equity, leading to an immediate share price decline, often referred to as the volatility-feedback effect (Karmakar, 2007:108-109).

It is possible that both the (financial) leverage and volatility-feedback effects could be at work concurrently. If for example there is an expectation in the market of an increase in

[16] Note that in cases where none of the first-order models [GARCH (1,1), TARCH (1,1,1) and EGARCH (1,1,1)] captured excess volatility, higher-order specifications were considered. Thus in some cases, the stationarity condition is ($\alpha_1+\alpha_2+\beta_1$). Results for such models are marked $^+$ in Table 3.

[17] In parentheses are the error distributions under which the models were estimated, e.g. Industrial Metals (GED) means the model for the Industrial metals sector was estimated assuming the generalised error distribution.

[18] The asymmetry coefficients are negative and significant and positive and significant in the EGARCH and the TARCH models respectively.

volatility, the result is that market participants would place more sell orders than buy orders. The end result is a drop in price to balance the buying and selling volume. Therefore an anticipated increase in volatility leads to an immediate price decline, as predicted by the volatility-feedback hypothesis. This drop in share prices will raise the leverage ratio, which, according to the leverage-effect hypothesis, brings about a further decline in price (Karmakar, 2007:109).

Irrespective of the source of the asymmetry, the implication affects the pricing of the securities and portfolio selection. From the results, the GARCH-in-mean and TARCH-in-mean models imply very different volatilities following a negative shock in comparison to EGARCH-in-mean models. If returns are linked to volatility, the EGARCH-in-mean model would suggest greater risk-premia since volatility increases indefinitely following negative news. On the other hand, the GARCH-in-mean and TARCH-in-mean models would imply lower risk-premia than the EGARCH-in-mean model, since volatility is not as explosive in the former models as in the latter model. Furthermore, the dynamic hedging strategies associated with the two sets of volatilities would differ significantly based on the volatility persistence (Karmakar, 2007:110).

4.2 Risk-Return Relationship

Table 3 also reports the coefficients for the risk-return trade-off for the estimated models. The results generally show that the risk-return relationship is negative and insignificant or positive and insignificant across the three models and error distributions, and across industries and sectors. Partly in line with a finding by Chinzara and Aziakpono (2009), volatility in the All Share Index, Benchmark Index and the AltX index returns is not a priced factor. The same result is echoed at an industrial level. At best it is evident that a few industries, such as Consumer Services, Industrials and Technology, show strong evidence of a negative relationship between risk and return. However, the results for the three models are mixed at sectoral level.[19]

Generally the GARCH-M model at a sectoral level does not show significant evidence of a positive risk-premium, with the exception of three sectors. Two sectors show significant evidence of a negative risk-premium. A similar picture is evident from the EGARCH-M model although in this case four sectors, three of which are similar to those in the GARCH-M model, show significant evidence of positive risk-premium. However, unlike in the GARCH-M model, a considerable number of sectors (12) show significant evidence of a negative risk-premium. The results for the TARCH-M model are not very different from the GARCH-M and EGARCH-M models except that five sectors show significant evidence of positive risk-premia, two similar to those in the GARCH-M and EGARCH-M models. Like in the EGARCH-M, twelve sectors show significant negative risk-return relationship, albeit that only four of those sectors are similar to those in the EGARCH-M model.

The existence of positive risk-premia in a few of the sectors is in line with empirical literature (cf. French *et al*., 1987; Campbell and Hentschel, 1991). On the other hand, although the negative risk-premia violate the fundamental principles of portfolio theory (cf.

[19] Notice that in some instances, the results are also mixed across the three error distributions.

Markowitz, 1952), it has been widely documented in other empirical studies (cf. LeBaron, 1989; Whitelaw, 1994; Fraser and Power, 1997; Lettau and Ludvigson, 2009; Balios, 2008). At least three reasons have been suggested to explain this negative risk-premia. Firstly, Chou *et al*. (1992), Whitelaw (1994) and Lettau and Ludvigson (2009) argue that such a finding may be due to misspecification of the time-varying nature of the risk-return relationship. Secondly, LeBaron (1989) and Balios (2008) attribute this finding to non-synchronisation of trading when the market is characterised by illiquidity and thin trading, forcing investors to forgo risk-premium in pursuit of a successful transaction. Thirdly, Koutmos *et al*. (1993) argue that the negative risk-premium can demonstrate the fact that local investors are not faced with foreign exchange risk, thus they will not demand an exchange rate risk-premium (i.e. returns are measured in South African rands). It is possible that once returns are converted to a foreign currency, such as the US dollar, the positive risk-premium will become evident (Koutmos *et al*., 1993). Since GARCH-type models have been widely credited for their ability to appropriately model time-varying risk, and given that the results are quite similar across the three models and error distributions, the first reason is strongly ruled out in the current study, although *with caution* it is our considered view that the second and third explanations are more plausible than the first explanation in the context of the current study.

4.3 Model Selection and Diagnostic Checks

The three models were compared across the three error distributional assumptions. In sectors where evidence of asymmetry was found, comparison was only between the EGARCH-M and TARCH-M, since the standard GARCH-in-mean model cannot capture asymmetry. In most of these cases, the TARCH-M model estimated under the GED seem to perform best (i.e. better TARCH-M models estimated based on Student–*t* and Gaussian and all the EGARCH-M). Evidently it is more stationary, captures volatility clustering and heteroscedasticity and has the minimum SIC. Specifically, as shown in Table 3, the TARCH-M under GED is the most appropriate model for 36 of the returns, TARCH-M under Student–*t* for seven of the returns, EGARCH-M under GED for one, and GARCH-M under GED for two returns best model for one sector respectively and the GARCH-M model was best for one sector.[20]

In order to confirm their appropriateness and robustness, the selected models were put under more diagnostic tests in addition to the ARCH LM test. The standardised residuals from these estimated models were examined for skewness, kurtosis, autocorrelation and heteroscedasticity and the results compared with those obtained for returns series as in Table 1. The descriptive statistics for the raw series and those of standardised residuals are reported in Table 4. Results reveal that kurtosis is now very low, indicating that the residuals now follow a normal distribution. Normality of the residuals is also confirmed by the skewness ratios which are now much closer to zero than those of the returns series. Furthermore, the LB(12) statistics for the standardised residuals are now insignificant, confirming that

[20] The selected models are denoted by an asterisk next to the SIC coefficient (*).

autocorrelation is no longer evident.[21] These diagnostic tests results confirm that the selected models are well specified.

Based on the selected model, volatility for each of the returns for the aggregate market, the industries and the sectors was estimated and the long-term trend was analysed. In what follows, the results of this analysis are discussed.

4.4 Trend of Volatility and Effects of Financial Crises and Political Shocks

To analyse the long-term trend of volatility, Equation (9) was estimated and the results are reported in Table 5. Generally the results show that volatility in the aggregate market, the industries and the sectors of the JSE has increased over the period of time (i.e. $\beta_2>0$ and is statistically significant). This is with the exception of some industries and sectors, for example the Chemicals sector, the Beverage and the Food Producers sector, the Travel and Leisure sector, the Food and Drug Retailers sector, the Health Care Equipment and Services sector, the Fixed Line Telecommunications sector, the General Industrials and Industrial sector, and the Consumer Goods industry sector, all of which show significant evidence of decreasing volatility over the period. The latter result is not very surprising given that most of the sectors are for basic necessities or important services, most of which do not have close substitutes. On the other hand, there are a number of possible explanations for the former result. For instance, volatility of most of the sectors within the mining industries could be due to the increasing USD/ZAR exchange rate volatility since the abandonment of exchange controls between 1994 and 2008 and the closure of some mines in early 2008 (Baxter, 2010). Oil price shocks between 2000 and 2008 might have also played a role in increasing the volatility of the stock market. Furthermore, the impact of factors such as the Asian and sub-prime financial crises cannot be ruled out.

The impact of latter three factors on the long-term trend of volatility was further analysed and results are also reported in Table 5.The results show there were structural breaks in the trend of volatility of the aggregate market and all the industries due to these events. However, when the analysis is disaggregated to sector level, the results show that not all sectors experienced structural breaks in volatility due to these events. For instance in the Materials industry, only the Forestry and Paper, Industrial Metals and Mining sectors showed a structural break in volatility during all three periods. In the Consumer Goods industry, Beverages was the only sector whose volatility structurally broke during these periods. In the Consumer Services industry, only the Food and Drug Retailers sector did not show evidence of structural break in volatility during all three periods. In the Health Care, Oil and Gas and Technology industries, there was no evidence of volatility structurally breaking due to these three shocks in the Pharmaceuticals and Biotechnology, Oil and Gas Producers and Software Computer and Services sectors. In the Industrials industry volatility all the sectors except Industrial Engineering and Electronic and Electrical Equipment showed structural breaks in all three periods. The pattern is different in the Financials industry, as volatility of all the sectors structurally broke during these periods.

[21] Only two sectors, Platinum & Precious Metals and Oil & Gas Producers, have standardised residuals whose LB2(12) is significant at 10%.

The Chemicals, General Mining, Platinum and Precious Metals, Food Producers, Food and Drug Retailers, Electronic and Electrical Equipment, Industrial Engineering and Fixed Line Telecommunications sectors did not react positively to the 9/11 attacks on the US. This was also the case with the volatility of the Mid Cap returns. The Automobile and Parts sector was the only sector that did not show any evidence of structural break in volatility reaction in any of the three periods. Due to unavailability of up-to-date data, the volatility of the Personal Goods, Household Goods and AltX series was only shown to have reacted to the current financial crisis.

There are a number of reasons why volatility breaks down during financial crises and international political shocks. Since South Africa is an emerging market, investors view it at par with other emerging markets, thus a financial crisis in an emerging market such as the Asian crisis is likely to be felt in South Africa directly. One the other hand, the channels through which a global crisis like the sub-prime crisis is felt in the South African stock market could be different from the Asian crisis, because the South African market is not well integrated into the major global financial markets (cf. Chinzara and Aziakpono, 2009). Thus the effects of a global shock are likely to be manifested indirectly through declining world commodity prices, shrinking export markets,[22] and reduced foreign direct investment and other financial inflows.[23] These pressures will lead the volatility in the macroeconomy, which in turn triggers volatility in stock prices and returns.[24] As for the case of a political shock, like the aftershocks of 9/11, volatility in the stock market is likely to emanate from the general fall in global investors' confidence and raised uncertainty on a global scale. As the results reveal, the effects of September 11 political shock were particularly felt in the Travel and Leisure sectors, implying that consumers became sceptical about travel. The issue of structural breaks in the behaviour of the South African stock markets has also been indirectly echoed by Morris, *et al.* (2009), although the latter study was primarily concerned with the presence of long memory in South African stock returns. They found that South African returns are subject to regime switches, with bearish regimes tending to be longer and more persistent than bullish regimes.

5. Conclusion

This study analysed the behaviour of volatility, the risk-return relationship, and the long-term trend of volatility on the South African equity market. Daily data for four JSE benchmark indices, nine industries, 33 sectors and two subsectors were used. Three GARCH-M family models were estimated under three error distributional assumptions, with estimations totalling 432 models. Results show that volatility at aggregate, industry and sector levels is generally persistent and there is significant evidence of asymmetry and leverage effects. Furthermore, except for a few sectors, volatility is generally not a priced

[22] Notice in Table 6 that South African exports decreased during the sub-prime crisis.
[23] In fact, capital outflow particularly affected the Automobile and Parts, and Mining and Retail sectors as these sectors depend heavily on foreign investment.
[24] Chinzara (2010) shows that volatility in the South African macroeconomy impacts on the volatility of the stock market.

factor. In fact, in some sectors significant evidence of a negative risk-premium was found. This can be a result of thin trading and illiquidity, and the fact that local investors are not exposed to foreign currency risk since returns are measured in local currency. It was further found that the TARCH-M under the GED is the most appropriate model for modelling volatility of most of the aggregate, industrial and sectoral returns of the JSE. Based on this model and distribution, conditional volatility was estimated and its long-term behaviour was analysed, with dummy variables added for the Asian and sub-prime financial crises and the post-September 11 political shocks, to examine whether these events caused structural breaks in the trend of the conditional volatility. The results generally show that both the financial crises and the political shock caused a structural break in the trend of volatility.

The findings of this study have implications for both investment and policy making. Firstly, the fact that volatility is generally not priced would have an implication for the factors to consider when investing. When investors are choosing in which sectors or stocks to invest, they need to consider more than risk (volatility). It is possible that factors such as skewness influence stock returns. Harvey and Siddique (2000) note that investors would prefer stocks whose returns are right-skewed to stocks whose returns are left-skewed. Investors also need to consider other factors such as book-to-market and the relative size of the firms. Secondly, the general increase in volatility in most of the industries and sectors is another issue of which investors and policy makers need to be aware. For investors it would be worthwhile to diversify their portfolios between risky and stable sectors, especially during global shocks and financial crises. Increasing volatility in the stock market is problematic for policy makers as it may cause large amounts of capital outflow, which could amplify financial instability, which might ultimately trigger macroeconomic instability. Although the effects of external political, macroeconomic shocks and global stock market volatilities are often difficult to avoid, given the increasing integration of world economies and financial markets, countries may minimise the effects of these spillovers by diversifying their exports, and maintaining macroeconomic and political discipline. Given the limited evidence that risk is priced, further research should try to incorporate the third moment (skewness) and the fourth moment (kurtosis) in the GARCH specification if the results vary.

REFERENCES

[1] Akaike, H. 1978. On newer statistical approaches to parameter estimation and structure determination. *International Federation of Automatic Control,* 3, 1877-1884.

[2] Balios, D. 2008. Intraday risk–return relationship and price patterns in the Athens stock exchange. *Journal of Money, Investment and Banking*, 3, 25-35.

[3] Baxter, R. 2010. The challenges and opportunities facing the South African mining industry. Chamber of Mines of South Africa, South Africa.

[4] Black, F. 1976. Studies of stock price volatility changes, Proceedings of the 1976 Meetings of the American Statistical Association. *Business and Economical Statistics Section,* 177-181.

[5] Brooks, C. 2002. *Introductory Econometrics for Finance*. Cambridge: Cambridge University Press.

[6] Campbell, J.Y. 1985. Stock returns and the term structure. *Journal of Financial Economics*, 18, 373-399.

[7] Campbell, J.Y. and Hentschel, L. 1991. No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of Financial Economics,* 31 (3), 281-318.

[8] Chang, T., Nieh, C. And Wei, C. 2006. Analysis of long-run benefits from international equity diversification between Taiwan and its major European trading partners: An empirical note. *Applied Economics*, 38, 2277-2283.

[9] Chinzara, Z. 2010. Macroeconomic uncertainty and emerging market stock market volatility: The case for South Africa. *ERSA Working Paper No*. 187.

[10] Chinzara, Z. and Aziakpono, M.J. 2009. Dynamic returns linkages and volatility transmission between South African and world major stock markets. *Studies in Economics and Econometrics*, 33 (3), 69-94.

[11] Chou, R., Engle R. F. and Kane A., 1992. Measuring risk aversion from excess returns on a stock index. *Journal of Econometrics*, 52, 201-224.

[12] Chowdhury, A.R. 1994. Stock Market Interdependencies: Evidence from the Asian NIEs. *Journal of Macroeconomics*, 16, 629-651.

[13] Christie, A.A. 1982. The stochastic behaviour of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics,* 10, 407-432.

[14] Davidson, R. and Mackinnon, J.G. 2004. *Econometric Theory and Methods*. New York: Oxford University Press.

[15] Edwards, S. and Garcia, M.G.P. 2008. *Financial markets volatility and performance in emerging markets*. University of Chicago Press.

[16] Engle, R.F., Lilien, D.M. and Robins, R.P. 1987. Estimating time varying risk-premia in the term structure: The ARCH-M model. *Econometrica,* 55 (2), 391-407.

[17] Fraser, P. and Power, D. 1997. Stock return volatility and information arrival: An empirical analysis of Pacific Rim, UK and US equity markets. *Applied Financial Economics,* 7, 241-253.

[18] French, K.R., Schwert, G.S. and Stambaugh, R.F. 1987. Expected stock return and volatility. *Journal of Financial Economics*, 19 (1), 3-29.

[19] Frömmel, M. and Menkhoff, L. 2003.Increasing exchange rate volatility during the recent float. *Applied Finance Economics*, 13 (12), 857-863.

[20] Glosten, L.R., Jagannathan, R. and Runkle, D.E. 1993. On the relation between expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48, 1779-1801.

[21] Gujarati, D. N., 2009. *Essentials of Econometrics* (5e). New York: McGraw-Hill Inc.

[22] Hansson, B. and Hordahl, P. 1998. Testing the conditional CAPM using multivariate GARCH-M. *Applied Financial Economics*, 8, 377-388.

[23] Harvey, C.R. 1991. The world price of covariance risk. *The Journal of Finance*, 46 (1), 111-157.

[24] HARVEY, C.R. and SIDDIQUE, A. 2000. Conditional skewness in asset pricing tests. *Journal of Finance*, 55, 1263-1295.

[25] Jochum, C. 1999. Volatility spillovers and the price of risk: Evidence from the Swiss stock market. *Empirical Economics*, 24, 303-22.

[26] Karmakar, M. 2007. Modelling conditional volatility of the Indian Stock market. *South Asia Economic Journal,* 30 (3), 21-37.

[27] Knight, J.L. and Satchell, S. 2001. *Return distributions in finance*. Oxford: Butterworth-Heinemann.

[28] Koop, G. 1994. Bayesian semi-nonparametric arch models. *The Review of Economics and Statistics*, 76 (1), 176-181.

[29] Koutmos, G., 1996. Modelling the dynamic interdependence of major European stock markets. *Journal of Business Finance and Accounting*, 23 (7), 975-988.

[30] Koutmos, G., Negakis, C. and Theodossiou, P. 1993. Stochastic behaviour of the Athens stock exchange. *Applied Financial Economics,* 3, 119-126.

[31] Kovačić, Z.J. 2008. Forecasting volatility on the Macedonian stock exchange. *International Research Journal of Finance and Economics,* 18, 182-212.

[32] LeBaron, B. 1989. Non-linear dynamics and stock returns, *Journal of Business*, 62, 311-337.

[33] Lanne, M. and Saikkonen, P. 2004. Modelling conditional skewness in stock returns. *EUI working paper*, No. 2005/14.

[34] Leon, N.K. 2008. An empirical study of the relation between stock market returns and volatility in the BVRM. *International Research Journal of Finance and Economics*, 14, 8-14.

[35] Leon, A., Nauve, J. and Rubio, G. 2005. The relationship between risk and expected return in Europe. *Journal of Banking & Finance,* 31, 495-512.

[36] Lettau, M., and Ludvigson, S.C. 2009. Measuring and modeling variation in the risk-return tradeoff. In Y. Aït-Sahalia and L.P. Hansen (eds.), *Handbook of Financial Economics*. Elsevier Science B.V. Amsterdam: North Holland.

[37] Ma, J., Nelson, C.R. and Startz, R. 2007. Spurious inference in the GARCH (1, 1) model when it is weakly identified. *Studies in Nonlinear Dynamics and Econometrics,* 11(1), 1-27.

[38] Magnus, F.J. and Fosu, O.E. 2006. Modelling and forecasting volatility of returns on the Ghana stock exchange using Garch models. *American Journal of Applied Sciences*, 3 (10), 2042-2048.

[39] Mangani, R. 2008. Modelling return volatility on the JSE Securities Exchange of South Africa. *African Finance Journal*, 10 (1), 55-71.

[40] Markowitz, H.M. 1959. *Portfolio selection: Efficient diversification of investments*. New York: John Wiley & Sons, Inc.

[41] Markowitz, H.M. 1952. Portfolio Selection. *The Journal of Finance* **7** (1), 77–91.

[42] Merton, R.C. 1973. An intertemporal asset pricing model. *Econometrica*, 41, 867-887.

[43] Mkhize, H. and Msweli-Mbanga, P. 2006. A critical review of the restructuring of the South African capital market. *International Review of Business Research Papers*, 2 (2), 80-91.

[44] Morris, Q., Van Vuuren, G.W. and Styger, P., 2009. Further evidence of long memory in the South African stock market, *South African Journal of Economics*, 77(1), 87-101.

[45] Nelson, C.R. and Startz, R. 2007. The Zero-Information-Limit-Condition and spurious inference of weakly identified models. *Journal of Econometrics*, 138(1), 47-62.

[46] Nelson, D.B. 1991. Conditional Heteroskedasticity in asset returns: A New Approach. *Econometrica*, 59 (2), 347-370.

[47] Pagan, A. and Hong, Y. 1991. Nonparametric Estimation and the Risk Premium. In W. Barnett, J. Powell and G. Tauchen (eds.), *Nonparametric and Seminonparametric Methods in Econometrics and Statistics*. Cambridge, UK: Cambridge University Press.

[48] POSHAKWALE, S. and MURINDE, V. 2001. Modelling the Volatility in East European Emerging Stock Markets: Evidence on Hungary and Poland. *Applied Financial Economics,* 11, 445-456.

[49] Rigobon, R. and Sack, B. 2003. Measuring the Reaction of Monetary Policy to the Stock Market. *Quarterly Journal of Economics*, 118, 639-669.

[50] SCHWARZ, G. 1978, Estimating the Dimension of a Model. *Annals of Statistics*, 6, 461-464.

[51] Saleem, K. 2007. Modeling time varying volatility and asymmetry of Karachi stock exchange (KSE). *International Journal of Economic Perspectives*, 1(1), 1-9.

[52] Theodossiou, P. and Lee, U. 1995. Relationship between volatility and expected returns across international stock markets. *Journal of Business Finance and Accounting,* 22(2), 289-300.

[53] Thomas, S.H. and Wickens, M.R. 1989. Non-Parametric estimates of the foreign exchange and equity risk-premia and tests of market efficiency. *CEPR Discussion Papers* No. 356.

[54] Turner, C.M, Startz, R. and Nelson, C.R. 1989. A Markov model of heteroskedasticity, risk, and learning in the stock market. *NBER working paper*, No. 2818.

[55] Tse, Y.K., 1998. The conditional heteroscedasticity of the yen-dollar exchange rate. *Journal of Applied Econometrics*, 13, 49-55.

[56] Whitelaw, R.F. 1994. Time variations and covariations in the expectation and volatility of stock market returns. *The Journal of Finance*, 49 (2), 515-541.

[57] Yu, J.M. and Hassan, K. 2008. Global and regional integration of the Middle East and North African (MENA) stock markets. *The Quarterly Review of Economics and Finance*, 48, 482-504.

[58] Zakoian, J.M. 1993. Threshold Arch models and asymmetries in volatility. *Journal of Applied Econometrics*, 8 (1), 31-49.

[59] Zivot, E. and Wang, J. 2006. *Modeling financial time series with S-PLUS*. New York: Springer.

APPENDICES: TABLES OF RESULTS

Table 1: Descriptive statistics and stationarity tests

	Mean	Median	Max.	Min.	Std.Dev	Skewness	Kurtosis	Jarque-Bera	LB(12)	$LB^2(12)$	ADF (Level)	KPSS(Level)
Basic Materials												
Basic Materials	0.017	0.000	4.848	-5.130	0.768	-0.020	8.263	4242.369[a]	67.886[a]	2864.921[a]	-35.1485[a]	0.145[a]
Chemicals	0.016	0.000	2.919	-4.656	0.529	-0.040	7.706	3392.829[a]	93.168[a]	338.211[a]	-38.1738[a]	0.144[a]
Forestry & Paper	-0.004	0.000	9.259	-8.368	1.140	0.146	9.426	6338.809[a]	50.861[a]	426.552[a]	-54.8889[a]	0.122[a]
Industrial Metals	0.025	0.000	8.939	-11.499	1.087	0.104	12.173	12894.430[a]	49.731[a]	350.451[a]	-54.8780[a]	0.178[a]
General Mining	0.015	0.000	6.697	-6.471	1.120	0.398	7.320	2955.623[a]	49.749[a]	984.773[a]	-56.4888[a]	0.219[a]
Mining	0.024	0.000	5.045	-5.197	0.823	-0.017	7.537	3153.184[a]	63.187[a]	2563.115[a]	-35.4296[a]	0.067[a]
Platinum & Precious Metals	0.032	0.000	5.342	-7.837	0.998	-0.332	6.830	2314.704[a]	106.642[a]	1308.915[a]	-36.5265[a]	0.084[a]
Consumer Goods												
Consumer Goods	0.026	0.000	6.172	-5.361	0.781	0.336	8.175	4170.637[a]	23.827[b]	521.021[a]	-58.5769[a]	0.051[a]
Automobile & Parts	-0.020	0.000	40.085	-39.747	1.372	-0.192	429.033	27800444.000[a]	483.882[a]	905.263[a]	-58.2119[a]	0.179[a]
Beverages	0.016	0.000	5.443	-5.890	0.778	0.040	7.269	2792.709[a]	30.482[a]	788.766[a]	-58.0677[a]	0.077[a]
Food Producers	0.018	0.003	3.847	-6.912	0.548	-0.579	14.581	20747.720[a]	40.174[a]	695.422[a]	-56.1169[a]	0.246[a]
Personal Goods	0.031	0.000	14.858	-4.972	0.981	3.477	59.314	125295.900[a]	27.085[a]	156.277[a]	-33.1210[a]	0.048[a]
Household Goods	-0.002	0.000	4.215	-4.934	1.155	0.020	4.724	115.720[a]	54.525[a]	398.845[a]	-20.5918[a]	0.116[a]
Consumer Services												
Consumer Services	0.014	0.013	2.933	-4.502	0.513	-0.752	9.792	7412.333[a]	124.98[a]	991.223[a]	-52.2216[a]	0.191[a]
Media	0.022	0.006	5.009	-8.217	0.888	-0.525	9.657	6956.925[a]	75.833[a]	1037.214[a]	-53.7212[a]	0.204[a]
Travel and Leisure	0.007	0.000	5.338	-4.635	0.640	-0.253	8.529	4721.492[a]	88.877[a]	430.541[a]	-53.1173[a]	0.342[a]
Food & Drug Retailers	0.032	0.000	7.901	-7.043	0.718	-0.146	12.631	14221.600[a]	21.113[b]	672.025[a]	-57.1265[a]	0.073[a]
General Retailers	0.014	0.008	2.866	-3.868	0.562	-0.392	6.706	2197.788[a]	202.86[a]	1082.716[a]	-50.2773[a]	0.122[a]
Financials												
Financials	0.015	0.000	3.524	-5.781	0.596	-0.428	10.000	7616.786[a]	85.993[a]	1266.423[a]	-52.7078[a]	0.089[a]
Banks	0.021	0.000	4.299	-6.064	0.785	-0.052	7.009	2463.041[a]	90.755[a]	1119.856[a]	-53.5091[a]	0.056[a]
Non-life Insurance	0.019	0.000	4.444	-5.006	0.626	-0.059	10.814	9353.620[a]	25.121[a]	334.981[a]	-59.1077[a]	0.097[a]
Life Insurance	0.007	0.000	4.348	-6.180	0.713	-0.261	8.387	4486.891[a]	42.326[a]	1091.425[a]	-56.4558[a]	0.079[a]
Real Estate	0.012	0.000	3.220	-2.877	0.444	0.019	8.072	3939.813[a]	40.964[a]	768.491[a]	-58.6488[a]	0.151[a]
General Financials	0.018	0.000	4.345	-7.467	0.730	-0.729	12.942	15464.370[a]	100.671[a]	1397.325[a]	-52.8560[a]	0.158[a]
Equity Investment Instrument	0.014	0.000	15.856	-5.293	0.682	3.004	88.458	1124110.000[a]	74.275[a]	74.142[a]	-35.8700[a]	0.079[a]
Health Care												
Health Care	0.017	0.000	4.827	-6.248	0.621	-0.289	9.691	6908.040[a]	42.751[a]	607.636[a]	-55.8723[a]	0.178[a]
Health Care Equipment & Services	0.031	0.000	5.828	-4.706	0.791	0.236	7.271	2828.572[a]	41.621[a]	449.131[a]	-55.9678[a]	0.169[a]
Pharmaceuticals & Biotechnology	0.034	0.000	9.925	-4.454	0.856	1.154	15.706	25543.140[a]	34.267[a]	49.6813[a]	-56.8247[a]	0.139[a]
Industrials												
Industrials	0.019	0.012	3.338	-5.913	0.566	-0.578	10.453	8712.553[a]	35.181[a]	692.371[a]	-55.6854[a]	0.110[a]
Construction & Materials	0.013	0.000	4.550	-5.238	0.650	-0.153	8.704	4997.495[a]	109.471[a]	587.283[a]	-52.1896[a]	0.579[a]
General Industrials	0.023	0.000	4.011	-6.446	0.637	-0.374	9.559	6674.509[a]	18.223[c]	608.825[a]	-57.5262[a]	0.094[a]
Electronic & Electrical Equipment	0.012	0.000	3.234	-4.504	0.620	-0.422	8.442	4644.961[a]	82.881[a]	1464.514[a]	-54.5328[a]	0.134[a]
Industrials Engineering	0.010	0.000	10.430	-14.364	0.674	-1.820	78.482	874697.500[a]	46.713[a]	587.3589[a]	-26.9095[a]	0.507[a]
Industrials Transport	0.003	0.000	4.037	-5.942	0.639	-0.626	9.554	6820.250[a]	48.315[a]	970.2861[a]	-55.3287[a]	0.138[a]
Support Services	0.010	0.000	3.883	-4.491	0.675	-0.285	7.192	2741.752[a]	22.919[b]	918.923[a]	-61.0217[a]	0.091[a]

Oil and Gas												
Oil & Gas	0.023	0.000	4.966	-5.155	0.832	0.033	7.530	3144.142[a]	50.888[a]	2311.191[a]	-56.2555[a]	0.060[a]
Oil & Gas Producers	0.026	0.000	6.239	-6.987	1.038	-0.038	6.802	2214.917[a]	55.235[a]	1078.338[a]	-37.0337[a]	0.052[a]
Technology												
Technology	0.010	0.000	6.373	-9.033	0.927	-0.685	12.356	13695.310[a]	74.333[a]	827.625[a]	-38.4416[a]	0.357[a]
Software Computer & Services	0.012	0.000	6.869	-9.176	0.976	-0.555	11.724	11845.730[a]	68.679[a]	751.747[a]	-54.5991[a]	0.408[a]
Telecommunications												
Telecommunications	0.030	0.004	8.534	-8.115	0.950	0.057	9.154	5803.355[a]	35.145[a]	754.347[a]	-56.0250[a]	0.074[a]
Fixed Line Telecommunications	0.020	0.000	9.392	-8.387	1.028	-0.008	9.034	5577.457[a]	44.728[a]	563.616[a]	-55.1629[a]	0.072[a]
Mobile Telecommunications	0.032	0.000	6.933	-5.315	1.194	0.328	5.666	293.459[a]	37.458[a]	198.941[a]	-24.4286[a]	0.116[a]
Benchmark												
All Share	0.019	0.009	3.224	-5.511	0.568	-0.502	9.512	6649.647[a]	49.692[a]	1371.736[a]	-56.0599[a]	0.063[a]
Mid Cap	0.021	0.023	2.058	-4.453	0.408	-1.153	13.013	16172.900[a]	223.421[a]	920.071[a]	-36.2782[a]	0.092[a]
Small Cap	0.018	0.029	1.723	-3.393	0.313	-1.824	17.201	32928.850[a]	630.672[a]	942.031[a]	-26.8487[a]	0.202[a]
Secondary Markets												
ALT X	-0.015	0.000	2.188	-3.171	0.573	-0.918	6.825	652.646[a]	37.279[a]	160.368[a]	-29.6414[a]	0.315[a]

Source: Author's own estimates
Notes:
The critical value for the ADF test at 1% critical value is -2.565592 and the KPSS 1% critical value is 0.739000. Thus [a] denotes rejection of a unit root/non-stationarity for both tests.
The lag order was determined by the SIC and the spectral estimation method is the Bartlett Kennel for ADF and KPSS respectively.
LB(12) and $LB^2(12)$ are Ljung-Box statistics for 12 lags calculated for returns and squared returns respectively.

Table 2: Serial Correlation Tests for the Mean Equations

	DW: C	B-G:C	DW: AR(1)	B-G :AR(1)	ARCH LM:C	ARCH LM:AR(1)
Basic Materials						
Basic Materials	1.801	8.771[a]	2.005	4.344	40.275[a]	17.475[a]
Chemicals	1.751	33.117[a]	2.012	5.292	65.114[a]	10.565[a]
Forestry & Paper	1.803	17.980[a]	2.000	1.838	35.641[a]	13.675[a]
Industrial Metals	1.803	18.947[a]	2.004	2.183	37.537[a]	14.366[a]
General Mining	1.860	9.277[a]	2.001	0.597	18.475[a]	10.913[a]
Mining	1.827	15.410[a]	2.003	5.392	30.589[a]	10.765[a]
Platinum & Precious Metals	1.725	39.370[a]	1.985	7.346c	77.151[a]	22.577[a]
Consumer Goods						
Consumer Goods	1.934	2.138	1.999	0.309	4.275	15.619[a]
Automobile & Parts	2.696	305.709[a]	2.109	8.067c	524.592[a]	97.582 [a]
Beverages	1.915	4.662	1.997	4.011	9.308[a]	9.010 [b]
Food Producers	1.848	10.938[a]	2.002	1.508	21.764[a]	13.017[b]
Personal Goods	2.164	0.109	1.997	1.357	6.502[b]	8.218[b]
Household Goods	1.865	12.295[a]	1.975	6.241	24.034[a]	20.133[a]
Consumer Services						
Consumer Services	1.706	40.873[a]	2.003	0.427	80.032[a]	10.854[a]
Media	1.761	26.712	2.001	0.303	52.697[a]	12.606[a]
Travel and Leisure	1.738	33.917[a]	1.992	2.402	66.659[a]	4.802[c]
Food & Drug Retailers	1.885	6.086[a]	1.995	0.593	12.141[a]	11.186[a]

General Retailers	1.632	66.044[a]	2.010	2.467	127.607[a]	14.932[a]
Financials						
Financials	1.723	35.821[a]	1.998	0.844	70.327[a]	11.688[a]
Banks	1.753	31.737[a]	1.989	5.894	62.447[a]	11.762[a]
Non-life Insurance	1.952	3.033[c]	1.999	2.154	6.060[a]	14.307[a]
Life Insurance	1.858	9.848[a]	1.997	2.153	19.607[a]	14.306[a]
Real Estate	1.936	5.743[a]	2.003	4.028	11.459[a]	8.046[b]
General Financials	1.729	34.431[a]	2.002	0.481	67.649[a]	10.963[a]
Equity Investment Instrument	1.814	19.183[a]	2.008	14.379	38.001[a]	28.566[a]
Health Care						
Health Care	1.839	12.314	1.998	0.652	24.484[a]	9.313[a]
Health Care Equipment & Services	1.844	13.481[a]	1.995	2.082	26.787[a]	14.165[a]
Pharmaceuticals & Biotechnology	1.874	7.406[a]	1.999	0.196	14.764[a]	14.996[a]
Industrials						
Industrials	1.832	12.844	1.999	0.422	25.531[a]	10.844[a]
Construction & Materials	1.704	41.143[a]	1.998	0.755	80.549[a]	11.511[a]
General Industrials	1.897	4.744[a]	1.999	0.268	9.472[a]	10.537[a]
Electronic & Electrical Equipment	1.790	21.111[a]	2.004	1.084	41.777[a]	12.169[a]
Industrials Engineering	2.097	6.581[a]	1.997	4.218	13.124[a]	18.427[a]
Industrials Transport	1.818	17.396[c]	2.004	2.598	34.494[a]	15.195[a]
Support Services	2.014	0.545	2.000	0.464	1.0901	10.929[a]
Oil and Gas						
Oil & Gas	1.852	10.229[a]	2.000	1.789	20.362[a]	13.579[a]
Oil & Gas Producers	1.849	11.526[a]	1.996	3.78	22.927[a]	17.553[a]
Technology						
Technology	1.783	26.751[a]	2.011	5.903	52.775[a]	11.781[b]
Software Computer & Services	1.792	23.956[a]	2.009	5.155	47.333[a]	10.292[a]
Telecommunications						
Telecommunications	1.845	12.447	1.995	2.519	24.746[a]	15.347[c]
Fixed Line Telecommunications	1.813	16.271	2.001	1.854	32.283[a]	13.708[a]
Mobile Telecommunications	1.994	7.522[a]	2.000	0.002	14.852[a]	14.882[a]
Benchmark						
All Share	1.846	12.288[a]	2.003	2.423	40.180[a]	17.102[b]
Mid Cap	1.592	83.900[a]	2.018	4.197	160.604[a]	8.384 [b]
Small Cap	1.466	153.174[a]	2.042	8.361c	282.996[a]	52.033
Secondary Markets						
ALT X	2.013	0.364	2.000	0.579	0.731	11.162

Source: Author's own estimates

Notes:

[a,b,c] implies coefficient is significant at 1%, 5% and 10% respectively.

DW:C, B-G:C: ARCH LM:C: denote Durbin-Watson, Breusch-Godfrey Serial Correlation, and Heteroscedasticity Test respectively for mean equation with a constant only.

DW:AR(1), B-G:AR(1): ARCH LM:AR(1): denote Durbin-Watson, Breusch-Godfrey Serial Correlation, and Heteroscedasticity Tests for mean equation with a constant and an autoregressive term.

Table 3: Estimated GARCH models

	GARCH-M					EGARCH-M					TARCH-M				
	δ	α+β	γ	F-LM	SIC	δ	α+β	γ	F-LM	SIC	δ	α+β	γ	F-LM	SIC
Basic Materials															
Basic Materials															
Gaussian Distribution	0.055	0.999^{+}		8.773^{a}	1.949	0.038	1.139^{+}	-0.021^{a}	21.397^{a}	1.952	0.046	0.956	0.074^{a}	2.157	1.949
Student -t Distribution	0.041	1.002^{+}		8.325^{a}	1.893	0.027	1.142^{+}	-0.030^{a}	25.284^{a}	1.892	0.025	0.938	0.107^{a}	2.231	1.893
Generalised Error Distribution	0.009	1.000^{+}		7.879^{a}	1.886	0.001	1.143^{+}	-0.026^{a}	22.518^{a}	1.886	0.015	0.938	0.102^{a}	2.273	1.887*
Chemicals															
Gaussian Distribution	-0.005	0.997		0.028	1.435	-0.019	1.015	-0.021^{a}	0.258	1.447	0.006	0.970	0.033^{a}	5.974	1.444
Student -t Distribution	0.019	0.997		0.892	1.335	-0.037	1.144	-0.036^{a}	2.966	1.341	0.011	0.981	0.028^{a}	1.147	1.335
Generalised Error Distribution	0.013	0.997		0.852	1.324	-0.033	1.122	-0.035^{a}	3.477	1.331	0.016	0.983	0.023^{a}	1.122	1.324*
Forestry & Paper															
Gaussian Distribution	0.076	0.996		1.166	2.893	0.012	1.117	-0.040^{a}	1.343	2.893	0.065	0.981	0.031^{a}	1.052	2.873
Student -t Distribution	0.051	0.994		1.152	2.719	0.011	1.117	-0.043^{a}	1.481	2.748	0.045	0.972	0.026^{a}	1.049	2.755
Generalised Error Distribution	0.001	1.004		0.368	2.724	0.015	1.134	-0.037^{a}	0.694	2.721	0.031	0.958	0.079^{a}	1.884	2.723*
Industrial Metals															
Gaussian Distribution	0.027	0.993		1.909	2.789	-0.011	1.094	-0.010^{a}	1.719	2.811	0.025	0.990	0.005^{a}	2.096	2.791
Student -t Distribution	0.015	0.996		1.816	2.479	-0.001	1.283	-0.003^{a}	0.109	2.559	0.031	0.992	0.024^{a}	2.231	2.565
Generalised Error Distribution	0.001	1.021		0.111	2.482	-0.003	1.236	-0.002^{a}	0.242	2.476	0.001	0.991	0.018^{a}	0.118	2.488*
General Mining															
Gaussian Distribution	0.083	0.998		2.236	2.813	0.093^{c}	1.128^{+}	-0.032^{a}	13.647^{a}	2.813	0.063	0.977^{+}	0.043^{a}	3.475^{b}	2.805
Student -t Distribution	0.017	1.002		0.154	2.737	0.071^{c}	1.134^{+}	-0.025^{a}	18.211^{a}	2.733	0.011	0.975	0.055^{a}	0.447	2.735
Generalised Error Distribution	0.000	0.999		0.447	2.726	0.059	1.132^{+}	-0.027^{a}	15.399^{a}	2.724	0.002	0.975	0.938^{a}	0.929	2.724*
Mining															
Gaussian Distribution	0.094^{c}	0.935^{+}		8.089^{a}	2.168	0.093^{c}	1.128^{+}	-0.032^{a}	13.647^{a}	2.168	0.071	0.978^{+}	0.037^{a}	5.873^{a}	2.167
Student -t Distribution	0.074^{c}	0.931^{+}		6.521^{a}	2.120*	0.071^{c}	1.134^{+}	-0.025^{a}	18.211^{a}	2.120	0.066	0.984^{+}	0.032^{a}	5.231^{a}	2.123
Generalised Error Distribution	0.062	0.933^{+}		7.001^{a}	2.124	0.059	1.132^{+}	-0.027^{a}	15.399^{a}	2.124	0.052	0.982^{+}	0.033^{a}	5.495^{a}	2.126
Platinum & Precious Metals															
Gaussian Distribution	0.090^{c}	0.997^{+}		4.016^{b}	2.551	0.110^{b}	1.124^{+}	-0.035^{a}	7.826^{a}	2.556	0.066	0.978^{+}	0.036^{a}	3.790^{b}	2.55
Student -t Distribution	0.105^{b}	1.002^{+}		3.336^{b}	2.510	0.111^{a}	1.136^{+}	-0.024^{b}	7.680^{a}	2.513	0.097^{b}	0.989^{+}	0.024^{c}	3.126^{b}	2.512
Generalised Error Distribution	0.110^{a}	1.000^{+}		6.659^{a}	2.508	0.127^{a}	1.132^{+}	-0.028^{c}	6.953^{a}	2.511	0.108^{b}	0.986^{+}	0.027^{c}	2.999^{c}	2.509*
Consumer Goods															
Consumer Goods															
Gaussian Distribution	0.026	0.990		1.619	2.347	0.016	1.141^{+}	-0.059^{a}	2.937^{c}	2.119	0.004	0.956	0.077^{a}	1.291	2.121
Student -t Distribution	-0.005	0.990		1.246	2.072	-0.009	1.137^{+}	-0.062^{a}	2.530^{c}	2.065	-0.009	0.950	0.088^{a}	2.513	2.068
Generalised Error Distribution	-0.005	0.989		1.108	2.063	-0.01	1.137^{+}	-0.064^{a}	2.441^{c}	2.056	-0.011	0.949	0.092^{a}	2.149	2.059*
Automobile & Parts															
Gaussian Distribution	0.310^{c}	0.680		0.081	3.041	0.148^{b}	1.212	0.164^{a}	0.007	2.987	0.161^{c}	1.311	-0.568^{a}	0.052	3.017

Student -t Distribution	0.000	908.436	0.003	1.770	-0.007	1.563	0.061	0.002	1.761	0.001	630.984	596.149	0.003	1.77
Generalised Error Distribution	0.000	1.714	0.002	1.329	0.618^{a}	-0.104	0.055^{a}	0.269	2.138	0.002	0.476	0.273	0.003	1.695*
Beverages														
Gaussian Distribution	-0.059	0.994	0.379	2.152	-0.071	1.076^{+}	-0.028^{a}	2.845^{c}	2.164	-0.06	0.982	0.026^{a}	0.984	2.151
Student -t Distribution	-0.046	0.992	1.539	2.092	-0.058	1.101	-0.037^{a}	1.636	2.089	-0.034	0.966	0.054^{a}	1.417	2.09
Generalised Error Distribution	-0.016	0.990	1.964	2.084	-0.015	1.086	-0.036^{a}	1.973	2.083	-0.009	0.965	0.052^{a}	1.863	2.082*
Food Producers														
Gaussian Distribution	-0.065	0.984^{+}	4.365^{b}	1.378	-0.138^{b}	1.084^{+}	-0.037^{a}	9.944^{a}	1.395	-0.087	0.945	0.060^{a}	9.395	1.378
Student -t Distribution	-0.038	0.986	1.435	1.306	-0.063	1.112^{+}	-0.035^{a}	5.950^{a}	1.308	-0.058	0.945	0.064^{a}	4.038	1.304
Generalised Error Distribution	-0.027	0.984	2.185	1.302	-0.045	1.098^{+}	-0.034^{a}	7.143^{a}	1.307	-0.043	0.942	0.062^{a}	5.142	1.301*
Personal Goods														
Gaussian Distribution	-0.074	1.030	0.322	2.560	-0.024	1.358	-0.035^{a}	0.111	2.535	0.214^{b}	0.889	0.211^{a}	0.057	2.551
Student -t Distribution	0.043	0.968	0.188	2.401	0.001	1.349	-0.024^{b}	0.006	2.357	0.136	0.875	0.189^{a}	0.054	2.397
Generalised Error Distribution	0.015	0.973	0.228	2.382	0.002	1.261	-0.028^{c}	0.061	2.342	0.008	0.857	0.260^{a}	0.054	2.378*
Household Goods														
Gaussian Distribution	0.073	0.957	0.149	2.967	0.085	1.206	-0.101^{a}	1.215	2.968	0.092	0.874	0.155^{a}	0.641	2.965
Student -t Distribution	0.043	0.960	0.262	2.960	0.069	1.225	-0.104^{a}	1.151	2.963	0.071	0.880	0.160^{b}	0.693	2.959
Generalised Error Distribution	0.019	0.963	0.267	2.948	0.031	1.224	-0.101^{a}	1.122	2.951	0.031	0.884	0.160^{b}	0.691	2.948*
Consumer Services														
Consumer Services														
Gaussian Distribution	-0.063	0.991	1.385	1.170	-0.153	1.136^{+}	-0.056^{a}	2.419^{c}	1.163	-0.131	0.944	0.087^{a}	0.689	1.162
Student -t Distribution	-0.055	0.993	1.616	1.112	-0.123^{a}	1.152^{+}	-0.044^{a}	3.422^{b}	1.108	-0.094^{c}	0.962	0.052^{a}	1.569	1.109*
Generalised Error Distribution	-0.063	0.992	1.987	1.116	-0.120^{a}	1.146^{+}	-0.049^{a}	2.625^{c}	1.114	-0.097^{b}	0.956	0.064^{a}	1.114	1.114
Media														
Gaussian Distribution	-0.068	0.986	1.755	2.290	-0.046	1.099	-0.016^{a}	0.393	2.294	-0.083	0.968	0.032^{a}	1.654	2.291
Student -t Distribution	-0.071	1.016	0.597	2.161	-0.085^{a}	1.165	-0.025^{b}	1.999	2.153	-0.081	0.993	0.038^{b}	0.246	2.161
Generalised Error Distribution	-0.072	1.001	0.984	2.150	-0.066^{b}	1.120	-0.019^{b}	0.042	2.147	-0.079	0.982	0.037^{a}	0.931	2.151*
Travel and Leisure														
Gaussian Distribution	-0.113^{c}	0.998	0.086	1.622	-0.154^{a}	1.049	-0.026^{a}	0.057	1.747	-0.161^{b}	0.977	0.035^{a}	13.853	1.75
Student -t Distribution	-0.050	1.000	0.572	1.632	-0.064	1.067	-0.022^{a}	0.326	1.639	-0.064	0.977	0.038^{a}	10.861	1.643
Generalised Error Distribution	0.001	0.998	0.483	1.622	-0.016	1.057	-0.023^{a}	0.172	1.628	-0.004	0.978	0.025^{a}	0.498	1.630*
Food & Drug Retailers														
Gaussian Distribution	-0.084	0.985	1.677	2.010	-0.126	1.122^{+}	-0.019^{a}	4.891^{a}	2.014	-0.088	0.973	0.018^{b}	1.454	2.011
Student -t Distribution	-0.056	0.987	1.555	1.896	-0.162	1.153^{+}	-0.006^{a}	4.009^{a}	1.914	-0.057	0.959	-0.001	2.996	1.924
Generalised Error Distribution	-0.002	0.986	0.592	1.898	-0.013	1.137^{+}	-0.016^{a}	3.579^{b}	1.897	0.003	0.978	0.015	0.429	1.900*
General Retailers														
Gaussian Distribution	-0.112	0.971	2.275	1.440	-0.174^{a}	1.117^{+}	-0.041^{a}	3.841^{b}	1.440	-0.134^{a}	0.971	0.035^{a}	2.579^{c}	1.436
Student -t Distribution	-0.052	0.991	1.735	1.388	-0.126^{b}	1.142^{+}	-0.037^{a}	2.900^{c}	1.388	-0.103^{c}	0.969	0.042^{a}	1.629	1.386
Generalised Error Distribution	-0.068	0.977	2.054	1.382	-0.118^{b}	1.137^{+}	-0.038^{a}	2.881^{c}	1.382	-0.098^{c}	0.966	0.042^{a}	1.653	1.380*
Financials														
Financials														
Gaussian Distribution	0.012	0.994	2.242	1.428	-0.041	1.167^{+}	-0.069^{a}	3.701^{b}	1.413	-0.034	0.959^{+}	0.077^{a}	3.329^{b}	1.417
Student -t Distribution	0.000	0.996	1.671	1.376	-0.036	1.177^{+}	-0.066^{a}	3.506^{b}	1.366	-0.035	0.944	0.101^{a}	1.987	1.370*
Generalised Error Distribution	0.002	0.993	1.639	1.380	-0.031	1.172^{+}	-0.067^{a}	3.254^{b}	1.370	-0.032	0.945	0.097^{a}	2.141	1.374
Banks														
Gaussian Distribution	0.065	0.980	1.953	2.085	0.041	1.141^{+}	-0.060^{a}	2.453^{c}	2.078	0.046	0.956	0.074^{a}	2.157	2.074
Student -t Distribution	0.036	0.990	1.967	2.035	0.019	1.170	-0.065^{a}	1.049	2.027	0.025	0.938	0.107^{a}	2.231	2.03

Generalised Error Distribution	0.031	0.986	1.841	2.034	0.013	1.161	-0.063^{a}	1.205	2.027	0.015	0.938	0.102^{a}	2.273	2.030*
Non-life Insurance														
Gaussian Distribution	-0.021	0.991	0.031	1.642	-0.103^{b}	1.201	-0.034^{a}	1.521	1.646	-0.079	0.960	0.061^{a}	0.131	1.623
Student -t Distribution	-0.035	0.995	1.873	1.465	-0.056^{c}	1.187	-0.048^{a}	7.214	1.463	-0.068^{c}	0.974	0.081^{a}	0.697	1.464
Generalised Error Distribution	0.001	0.967	1.972	1.432	-0.067^{b}	1.138	-0.033^{a}	12.284	1.418	-0.001	0.890	0.131^{a}	2.202	1.436*
Life Insurance														
Gaussian Distribution	0.001	0.996^{+}	2.646^{c}	1.889	-0.027	1.138	-0.037^{a}	4.804	1.886	-0.034	0.973^{+}	0.042^{a}	2.345^{c}	1.886
Student -t Distribution	-0.021	0.997^{+}	3.508^{b}	1.823	-0.041	1.147^{+}	-0.031^{a}	5.782^{a}	1.821	-0.042	0.972	0.046^{a}	2.087	1.823
Generalised Error Distribution	-0.022	0.996	2.072	1.822	-0.045	1.145^{+}	-0.034^{a}	4.814^{a}	1.820	-0.041	0.969	0.050^{a}	2.141	1.822*
Real Estate														
Gaussian Distribution	-0.013	1.000	1.322	0.965	-0.016	1.100	0.992^{a}	1.981	0.972	-0.032	0.990	0.021	1.078	0.964
Student -t Distribution	-0.029	1.002	1.359	0.852	-0.019	1.108	-0.015^{c}	1.399	0.884	-0.016	0.995	0.016^{a}	2.504	0.882
Generalised Error Distribution	-0.025	1.000	1.392	0.870	-0.017	1.103	-0.017^{b}	1.222	0.874	-0.029	0.991	0.019^{a}	1.209	0.871*
General Financials														
Gaussian Distribution	0.084	0.943	0.346	1.893	0.004	1.205^{+}	-0.054^{a}	2.730^{c}	1.899	0.029	0.897	0.088^{a}	0.337	1.891
Student -t Distribution	0.039	0.980	0.222	1.813	-0.006	1.218^{+}	-0.036^{a}	4.502^{b}	1.811	0.016	0.941	0.071^{a}	0.151	1.814
Generalised Error Distribution	0.015	0.966	0.214	1.802	0.012	1.213^{+}	-0.041^{a}	3.432^{b}	1.800	-0.003	0.926	0.078^{a}	0.138	1.802*
Equity Investment Instruments														
Gaussian Distribution	0.001	0.989	0.142	1.638	-0.052	1.162	-0.045^{a}	0.377	1.633	-0.130^{b}	0.954	0.052^{a}	1.757	1.633
Student -t Distribution	-0.036	0.993	0.159	1.513	-0.051	1.117	-0.032^{a}	0.912	1.502	-0.101^{c}	0.950	0.062^{a}	1.467	1.511
Generalised Error Distribution	-0.001	0.989	0.029	1.500	-0.004	1.129	-0.038^{a}	0.758	1.492	-0.090^{c}	0.949	0.060^{a}	1.477	1.498*
Health Care														
Health Care														
Gaussian Distribution	-0.065	0.993	9.702	1.679	-0.086	1.085^{+}	-0.026^{a}	4.304^{a}	1.687	-0.084	0.983	0.019^{a}	1.682	1.67
Student -t Distribution	-0.043	0.965	0.178	1.599	-0.068	1.105^{+}	-0.034^{a}	2.306^{c}	1.600	-0.053	0.975	0.035^{a}	0.378	1.597
Generalised Error Distribution	-0.054	0.992	0.548	1.596	-0.057	1.096^{+}	-0.030^{a}	2.774^{c}	1.598	-0.056	0.978	0.028^{b}	0.745	1.593*
Health Care Equipment & Services														
Gaussian Distribution	-0.079	0.983	2.233	2.206	-0.131^{b}	1.108	-0.019^{a}	0.374	2.208	-0.082	0.979	0.025^{a}	0.369	2.204
Student -t Distribution	-0.099	0.991	1.694	2.125	-0.117^{b}	1.125	-0.021^{b}	0.174	2.122	-0.103^{c}	0.973	0.037^{a}	1.627	2.126
Generalised Error Distribution	-0.001	0.982	0.803	2.094	0.006	1.133	-0.023^{a}	0.061	2.091	-0.002	0.964	0.048^{c}	0.943	2.095*
Pharmaceutical & Biotechnology														
Gaussian Distribution	-0.103	0.934	0.035	2.422	-0.114^{c}	1.131	-0.064^{a}	0.134	2.420	-0.114	0.922	0.075^{a}	0.042	2.419
Student -t Distribution	-0.019	1.256	0.042	2.128	-0.011	1.369	-0.138^{a}	0.022	2.114	-0.005	0.988	0.180^{a}	2.435	2.110*
Generalised Error Distribution	-0.011	0.991	0.091	1.975	0.051	1.600	-0.252^{a}	0.919	1.142	0.001^{a}	2.804	1.331^{a}	0.286	0.19
Industrials														
Industrials														
Gaussian Distribution	-0.024	0.981	2.001	1.467	-0.104^{c}	1.130	-0.068^{a}	1.957	1.458	-0.079	0.928	0.101^{a}	1.415	1.455
Student -t Distribution	-0.049	0.981	1.621	1.412	-0.105^{c}	1.149^{+}	-0.059^{a}	3.114^{b}	1.408	-0.079	0.936	0.082^{a}	1.465	1.408
Generalised Error Distribution	-0.057	0.979	2.167	1.413	-0.094^{b}	1.143	-0.064^{a}	2.155	1.408	-0.079	0.931	0.091^{a}	1.286	1.407*
Construction & Materials														
Gaussian Distribution	-0.159^{a}	0.999	1.253	1.747	-0.172^{a}	1.041	-0.008^{a}	2.234	1.766	-0.164	0.997	0.004^{c}	1.072	1.749
Student -t Distribution	-0.157^{b}	0.991	0.183	1.660	-0.170^{a}	1.154	-0.011^{a}	0.338	1.659	-0.162	0.982	0.017^{a}	0.18	1.661
Generalised Error Distribution	-0.118^{b}	0.992	1.127	1.662	-0.136^{a}	1.115	-0.014^{a}	1.761	1.663	-0.129	0.995	0.004^{a}	0.745	1.659*
General Industrials														
Gaussian Distribution	-0.010	0.988	0.732	1.765	-0.054	1.100^{+}	-0.059^{a}	2.625^{c}	1.757	-0.046	0.930	0.093^{a}	2.251	1.755
Student -t Distribution	-0.032	0.985	1.232	1.704	-0.043	1.118^{+}	-0.049^{a}	3.307^{b}	1.701	-0.048	0.942^{+}	0.069^{a}	2.652^{b}	1.702
Generalised Error Distribution	-0.036	0.985	0.881	1.704	-0.048	1.114^{+}	-0.054^{a}	2.408^{c}	1.700	-0.055	0.936	0.080^{a}	2.171	1.700*

Electronic & Electrical Equipment															
Gaussian Distribution	-0.096	0.980	2.276	1.625	-0.191	1.100	-0.038[a]	0.044	1.620	-0.130[b]	0.954	0.052[a]	1.757	1.621
Student -t Distribution	-0.080	0.982	1.839	1.554	-0.146	1.104	-0.040[a]	0.446	1.548	-0.101[c]	0.950	0.062[a]	1.467	1.552
Generalised Error Distribution	-0.075	0.980	1.934	1.545	-0.135	1.100	-0.039[a]	0.262	1.540	-0.090[c]	0.949	0.060[a]	1.477	1.543*
Industrial Engineering															
Gaussian Distribution	-0.012	0.981	0.489	1.735	-0.069	1.209	-0.065[a]	0.358	1.727	-0.061	0.916	0.119[a]	0.388	1.725
Student -t Distribution	0.003	1.240	0.765	1.470	-0.008	1.384	-0.097[a]	0.465	1.461	-0.011	1.056	0.322[b]	0.816	1.468
Generalised Error Distribution	0.000	2.245	1.418	1.130	0.141	0.061	-0.086[a]	11.935	1.378*	0.001[a]	1.812	1.073[c]	6.926	1.378
Industrial Transport															
Gaussian Distribution	-0.020	0.966	1.564	1.735	-0.081	1.124	-0.054[a]	1.495	1.727	-0.062	0.925	0.081[a]	1.674	1.728
Student -t Distribution	0.027	0.982	0.165	1.628	-0.022	1.221	-0.059[a]	0.593	1.625	0.152	0.926	0.0875	1.685	1.695
Generalised Error Distribution	0.031	0.969	0.225	1.619	-0.012	1.195	-0.059[a]	0.953	1.617	0.007	0.920	0.093[a]	0.342	1.617*
Support Services															
Gaussian Distribution	-0.024	0.984	2.759	1.858	-0.046	1.107[+]	-0.048[a]	3.531[b]	1.855	-0.046	0.951	0.061[a]	2.296	1.854
Student -t Distribution	-0.010	0.992	0.285	1.809	-0.029	1.113[+]	-0.044[a]	3.749[b]	1.811	-0.058	0.965	0.045[a]	0.404	1.809
Generalised Error Distribution	-0.019	0.991	0.392	1.799	-0.031	1.110[+]	-0.046[a]	3.549[b]	1.800	-0.022	0.966	0.046[a]	0.223	1.798*
Oil and Gas															
Oil & Gas															
Gaussian Distribution	0.072	0.999[+]	12.765[a]	2.163	0.069	1.122[+]	-0.024[a]	21.021[a]	2.167	0.054	0.984[+]	0.028[a]	10.299[a]	2.163
Student -t Distribution	0.050	1.002[+]	9.371[a]	2.107	0.046	1.132[+]	-0.024[a]	21.786[a]	2.107	0.043	0.987	0.030[b]	8.001	2.110*
Generalised Error Distribution	0.044	1.000[+]	10.052[a]	2.109	0.046	1.128[+]	-0.023[a]	20.154[a]	2.111	0.038	0.985	0.028[a]	8.568	2.111
Oil & Gas Producers															
Gaussian Distribution	-0.022	0.978[+]	7.526[a]	2.716	-0.019	1.083	-0.020[a]	6.962	2.721	-0.043	0.986	0.022[a]	1.483	2.707
Student -t Distribution	-0.017	0.980[+]	9.104[a]	2.673	-0.009	1.091	-0.025[a]	7.086	2.673	-0.019	0.981	0.028[b]	1.205	2.672
Generalised Error Distribution	-0.007	0.976[+]	6.212[a]	2.658*	-0.004	1.087	-0.024[a]	5.436	2.660	-0.018	0.982	0.026[b]	0.812	2.657
Technology															
Technology															
Gaussian Distribution	-0.150[a]	0.995	0.145	2.353	-0.222	1.094	-0.032[a]	1.641	2.365	-0.172[a]	0.984	0.022[a]	0.127	2.352
Student -t Distribution	-0.075[c]	0.993	1.277	2.237	-0.108[a]	1.243	-0.035[b]	1.826	2.232	-0.091[b]	0.967	0.053[b]	1.552	2.237
Generalised Error Distribution	-0.023	0.986	1.563	2.234	-0.067	1.136	-0.032[a]	0.255	2.231	-0.036	0.961	0.050[b]	1.846	2.235*
Software Computer & Services															
Gaussian Distribution	-0.116[b]	0.992	0.029	2.510	-0.189[a]	1.110	-0.030[a]	1.249	2.490	-0.140[a]	0.980	0.024	0.029	2.498
Student -t Distribution	-0.078[c]	0.993	0.796	2.365	-0.109	1.262	-0.039[a]	0.777	2.359	-0.093[b]	0.961	0.066	0.933	2.366
Generalised Error Distribution	-0.018	0.981	0.923	2.362	-0.045	1.244	-0.036[b]	1.084	2.362	-0.026	0.951	0.065	1.084	2.362*
Telecommunications															
Telecommunications															
Gaussian Distribution	-0.023	0.994	1.025	2.467	-0.044	1.154[+]	-0.032[a]	3.030[b]	2.462	-0.038	0.976	0.033[a]	1.104	2.467
Student -t Distribution	-0.044	1.003	0.848	2.402	-0.054	1.189	-0.027[b]	1.876	2.397	-0.051	0.984	0.037[a]	0.701	2.403
Generalised Error Distribution	-0.039	0.997	1.445	2.393	-0.043	1.174	-0.031[b]	2.176	2.389	-0.042	0.978	0.038[b]	1.236	2.394*
Fixed Line Telecommunications															
Gaussian Distribution	0.013	0.974	0.761	2.693	-0.075	1.163	-0.034[a]	1.843	2.687	0.001	0.955	0.040[a]	1.028	2.693
Student -t Distribution	0.007	0.993	0.124	2.592	0.007	1.215	-0.014[a]	0.232	2.585	0.005	0.986	0.013	0.109	2.594
Generalised Error Distribution	0.002	0.983	0.181	2.565	0.024	1.191	-0.024[a]	0.483	2.558	0.001	0.969	0.027	0.117	2.567*
Mobile Telecommunications															
Gaussian Distribution	-0.043	0.990[+]	3.507[b]	3.093	0.137	1.020	-0.093[a]	6.515	3.076	0.042	0.935	0.097[a]	2.853	3.086
Student -t Distribution	-0.139	0.988[+]	2.898[c]	3.074	0.054	1.032	-0.094[a]	4.974	3.066	-0.012	0.921	0.120[a]	1.474	3.071

Generalised Error Distribution	-0.128	0.973[+]	2.811[c]	3.065	0.029	1.027[+]	-0.094[a]	5.004[a]	3.055	-0.011	0.927	0.113[a]	1.875	3.054*
Benchmark														
All Share														
Gaussian Distribution	0.047	0.995[+]	3.167[b]	1.383	-0.009	1.162[+]	-0.072[a]	4.970[a]	1.381	0.001	0.949	0.084[a]	2.243	1.372
Student -t Distribution	0.036	0.994	2.012	1.337	-0.001	1.160[+]	-0.060[a]	7.900[a]	1.335	0.015	0.954	0.072[a]	2.091	1.332*
Generalised Error Distribution	0.031	0.994	2.121	1.344	-0.007	1.162[+]	-0.066[a]	3.036[b]	1.342	0.011	0.951	0.078[a]	2.076	1.337
Mid Cap														
Gaussian Distribution	-0.044	0.982	1.465	0.670	-0.136[b]	1.204[+]	-0.073[a]	2.855[c]	0.669	-0.126[c]	0.925	0.103[a]	0.627	0.662
Student -t Distribution	-0.024	0.985[+]	3.925[b]	0.606	-0.085	1.168[+]	-0.978[a]	7.129[a]	0.607	-0.074	0.947[+]	0.063[a]	2.359[c]	0.605*
Generalised Error Distribution	-0.044	0.985[+]	2.817[c]	0.611	-0.108[b]	1.178	-0.056[a]	5.117	0.651	-0.046	0.940	0.072[a]	1.368	0.606
Small Cap														
Gaussian Distribution	-0.159	0.978	0.537	0.120	-0.314[a]	1.235	-0.101[a]	0.631	0.101	-0.298[a]	0.882	0.173[a]	0.462	0.104
Student -t Distribution	-0.119	0.978	1.334	0.008	-0.233[a]	1.185	-0.053[a]	2.851	0.003	-0.195[a]	0.936	0.065[a]	0.937	0.007*
Generalised Error Distribution	-0.092	0.972	0.611	0.024	-0.233[a]	1.196	-0.068[a]	1.521	0.018	-0.187[a]	0.915	0.094[a]	0.332	0.022
Secondary Markets														
ALT X														
Gaussian Distribution	-0.141	0.969	0.939	1.597	-0.181	1.222	-0.046[a]	1.244	1.593	-0.254[c]	0.919	0.088[a]	0.925	1.608
Student -t Distribution	0.087	0.952	0.865	1.531	-0.005	1.200	-0.035[a]	1.129	1.530	0.949[a]	0.918	0.097[a]	0.316	1.601
Generalised Error Distribution	0.039	0.955	0.862	1.526	0.019	1.217	-0.034[a]	1.134	1.529	0.018	0.924	0.044[a]	0.913	1.540*

Source: Author's own estimates

Notes: [a,b,c] implies coefficient is significant at 1%, 5% and 10% respectively.

* next to the SIC coefficient represents the selected model.

δ is the coefficient which shows the risk-return relationship, $\alpha+\beta<0$ is the condition for stationarity of the models, γ is the Coefficient of asymmetry. Note this only applies to EGARCH-M and TARCH-M models, F-LM represents the test for ARCH effects, SIC represents the Schwarz information criterion.

Table 4: Further Diagnostic Checks for the Selected Models

	Raw Returns series					Standardised Residuals from Selected Models				
	Mean	**Std.Dev**	**Skewness**	**Kurtosis**	**LB(12)**	**Mean**	**Std.Dev**	**Skewness**	**Kurtosis**	**LB(12)**
Basic Materials										
Basic Materials	0.017	0.768	-0.020	8.263	67.886[a]	-0.002	1.000	-0.070	4.964	21.928
Chemicals	0.016	0.529	-0.040	7.706	93.168[a]	0.018	1.000	0.009	6.247	10.002
Forestry & Paper	-0.004	1.140	0.146	9.426	50.861[a]	-0.008	0.983	-0.067	7.193	17.585
Industrial Metals	0.025	1.087	0.104	12.173	49.731[a]	0.033	1.030	0.918	17.540	5.8267
General Mining	0.015	1.120	0.398	7.320	49.749[a]	0.013	0.995	0.343	6.227	9.3587
Mining	0.024	0.823	-0.017	7.537	63.187[a]	-0.001	1.001	0.015	4.883	19.715
Platinum & Precious Metals	0.032	0.998	-0.332	6.830	106.642[a]	-0.031	0.990	-0.267	6.801	22.132c
Consumer Goods										
Consumer Goods	0.026	0.781	0.336	8.175	23.827[b]	0.028	0.997	0.223	4.957	17.638
Automobile & Parts	-0.020	1.372	-0.192	429.033	483.882[a]	-0.071	1.938	-20.808	717.794	0.045
Beverages	0.016	0.778	0.040	7.269	30.482[a]	0.007	0.999	0.030	6.142	18.635
Food Producers	0.018	0.548	-0.579	14.581	40.174[a]	0.013	1.004	0.005	5.777	15.922

Personal Goods	0.031	0.981	3.477	59.314	27.085[a]	0.030	1.000	1.106	15.036	2.798
Household Goods	-0.002	1.155	0.020	4.724	54.525[a]	-0.004	0.997	0.008	3.621	13.374
Consumer Services										
Consumer Services	0.014	0.513	-0.752	9.792	124.98[a]	0.005	1.008	-0.521	6.508	9.661
Media	0.022	0.888	-0.525	9.657	75.833[a]	0.037	1.008	-0.147	9.592	8.7367
Travel and Leisure	0.007	0.640	-0.253	8.529	88.877[a]	0.016	1.001	0.213	7.478	17.229
Food & Drug Retailers	0.032	0.718	-0.146	12.631	21.113[b]	0.053	0.979	-0.328	6.414	16.675
General Retailers	0.014	0.562	-0.392	6.706	202.86[a]	0.008	1.003	-0.266	5.176	9.7553
Financials										
Financials	0.015	0.596	-0.428	10.000	85.993[a]	0.006	1.005	-0.180	5.431	11.059
Banks	0.021	0.785	-0.052	7.009	90.755[a]	0.008	1.002	0.023	5.313	11.802
Non-life Insurance	0.019	0.626	-0.059	10.814	25.121[a]	0.046	0.997	0.131	7.564	10.864
Life Insurance	0.007	0.713	-0.261	8.387	42.326[a]	-0.002	1.002	-0.171	5.379	17.508
Real Estate	0.012	0.444	0.019	8.072	40.964[a]	0.021	1.000	0.002	5.560	6.723
General Financials	0.018	0.730	-0.729	12.942	100.671[a]	0.021	0.998	-0.103	5.492	8.419
Equity Investment Instrument	0.014	0.682	3.004	88.458	74.275[a]	0.030	0.998	0.161	7.699	19.773
Health Care										
Health Care	0.017	0.621	-0.289	9.691	42.751[a]	0.012	1.003	-0.021	5.832	18.293
Health Care Equipment & Services	0.031	0.791	0.236	7.271	41.621[a]	0.056	0.975	0.361	5.610	10.044
Pharmaceuticals & Biotechnology	0.034	0.856	1.154	15.706	34.267[a]	0.003	0.069	-0.733	59.129	14.837
Industrials										
Industrials	0.019	0.566	-0.578	10.453	35.181[a]	0.005	1.004	-0.226	5.355	16.658
Construction & Materials	0.013	0.650	-0.153	8.704	109.471[a]	0.033	1.008	0.139	6.893	4.6533
General Industrials	0.023	0.637	-0.374	9.559	18.223[c]	0.010	1.002	-0.177	5.442	20.115
Electronic & Electrical Equipment	0.012	0.620	-0.422	8.442	82.881[a]	0.024	1.000	-0.117	5.240	17.581
Industrials Engineering	0.010	0.674	-1.820	78.482	46.713[a]	0.003	0.100	-2.125	43.059	18.591
Industrials Transport	0.003	0.639	-0.626	9.554	48.315[a]	-0.001	1.002	-0.222	6.549	10.341
Support Services	0.010	0.675	-0.285	7.192	22.919[b]	0.005	0.997	-0.209	5.256	11.244
Oil and Gas										
Oil & Gas	0.023	0.832	0.033	7.530	50.888[a]	0.013	1.035	-0.015	6.805	19.151
Oil & Gas Producers	0.026	1.038	-0.038	6.802	55.235[a]	0.013	1.035	-0.015	6.796	23.113[c]
Technology										
Technology	0.010	0.927	-0.685	12.356	74.333[a]	0.026	1.014	0.524	13.947	7.997
Software Computer & Services	0.012	0.976	-0.555	11.724	68.679[a]	0.030	1.014	0.452	14.571	6.582
Telecommunications										
Telecommunications	0.030	0.950	0.057	9.154	35.145[a]	0.015	0.998	0.045	5.339	17.029
Fixed Line Telecommunications	0.020	1.028	-0.008	9.034	44.728[a]	0.024	0.985	-0.006	6.225	15.311
Mobile Telecommunications	0.032	1.194	0.328	5.666	37.458[a]	0.020	0.998	0.251	3.885	11.032
Benchmark										
All Share	0.019	0.568	-0.502	9.512	49.692[a]	-0.014	1.002	-0.296	5.003	13.429
Mid Cap	0.021	0.408	-1.153	13.013	223.421[a]	0.012	1.008	-0.325	5.441	6.728
Small Cap	0.018	0.313	-1.824	17.201	630.672[a]	0.031	1.021	-0.818	7.693	6.9424
Secondary Markets										
ALT X	-0.015	0.573	-0.918	6.825	37.279[a]	-0.020	1.003	-0.582	5.990	8.238

Source: Author's own estimates

Notes: [a,b,c] implies coefficient is significant at 1%, 5% and 10% respectively.

LB(12) and LB^2(12) are Ljung-Box statistics for 12 lags calculated for returns and squared returns respectively.

Table 5: Trend in volatility and effects of political and financial shocks

	Constant	Trend	Dum1	Dum2	Dum3
Basic Materials					
Basic Materials	0.117[a]	0.00013[a]	0.453[a]	0.297[a]	2.002[a]
Chemicals	0.334[a]	-0.00002[a]	0.383[a]	0.013	0.234[a]
Forestry & Paper	1.356[a]	-0.00008[a]	2.056[a]	0.561[a]	3.328[a]
Industrial Metals	0.803[a]	0.00008[a]	0.746[a]	1.901[a]	2.858[a]
General Mining	1.072 [a]	-0.00003[a]	1.108[a]	0.015	2.938[a]
Mining	0.130[a]	0.00018[a]	0.544[a]	0.507[a]	1.971[a]
Platinum & Precious Metals	0.203 [a]	0.00033[a]	0.864[a]	0.082	2.360[a]
Consumer Goods					
Consumer Goods	0.658[a]	0.00003[a]	0.658[a]	0.701[a]	0.217[a]
Automobile & Parts	-0.471	0.00089[a]	0.502	-0.396	0.198
Beverages	0.634[a]	0.00002[a]	1.030[a]	0.308[a]	0.609[a]
Food Producers	0.387[a]	0.00003	0.788[a]	0.003	0.178[a]
Personal Goods	0.531[a]	0.00049[a]	n/a	n/a	0.292[a]
Household Goods	0.656[a]	0.00086[a]	n/a	n/a	0.648[a]
Consumer Services					
Consumer Services	0.236[a]	0.00003[a]	0.513[a]	0.074[a]	0.263[a]
Media	0.755[a]	0.00005[a]	1.204[a]	0.343[a]	0.707[a]
Travel and Leisure	0.517[a]	-0.00003[a]	0.747[a]	0.365[a]	0.244[a]
Food & Drug Retailers	0.707[a]	-0.00003[a]	0.760[a]	0.001	0.187[a]
General Retailers	0.233[a]	0.00004[a]	0.301[a]	0.113[a]	0.329[a]
Financials					
Financials	0.303[a]	0.00006[a]	0.916[a]	0.114[a]	0.511[a]
Banks	0.468[a]	0.00011[a]	1.229[a]	0.220[a]	0.859[a]
Nonlife Insurance	0.319[a]	0.00006[a]	0.580[a]	0.109[b]	0.498[a]
Life Insurance	0.256[a]	0.00009[a]	0.624[a]	0.279[a]	0.977[a]
Real Estate	0.173[a]	0.00003[a]	0.347[a]	0.129[a]	0.216[a]
General Financials	0.390[a]	0.00008[a]	0.955[a]	0.132[c]	0.762[a]
Equity Investment Instrument	0.541[a]	-0.00003[b]	1.272[a]	0.112[b]	0.944[a]
Health Care					
Health Care	0.412[a]	0.00004[a]	0.832[a]	0.114[a]	0.207[a]
Health Care Equipment & Services	0.828[a]	-0.00001	1.173[a]	-0.097[b]	0.219[a]
Pharmaceuticals & Biotechnology	0.709[a]	0.01130[a]	122.758[a]	84.039[a]	124.686[a]
Industrials					
Industrials	0.349[a]	0.00001[b]	0.625[a]	0.107[a]	0.287[a]
Construction & Materials	0.329[a]	0.00002[a]	0.504[a]	-0.070[a]	0.751[a]
General Industrials	0.440[a]	0.00002[b]	0.699[a]	0.162[a]	0.301[a]
Electronic & Electrical Equipment	0.343[a]	0.00002	0.648[a]	-0.001	0.843[a]
Industrials Engineering	0.505[a]	0.00079	70.330[a]	-5.104	188.713[a]

Industrials Transport	0.351[a]	0.00003[a]	0.619[a]	0.125[a]	0.700[a]
Support Services	0.393[a]	0.00005[a]	0.616[a]	0.188[a]	0.476[a]
Oil and Gas					
Oil & Gas	0.058[b]	0.00022[a]	0.607[a]	0.453[a]	2.077[a]
Oil & Gas Producers	0.868[a]	0.00013[a]	1.942[a]	0.499[a]	1.733[a]
Technology					
Technology	1.098[a]	-0.00011[a]	0.841[a]	0.986[a]	0.892[a]
Software Computer & Services	1.254[a]	-0.00013[a]	0.857[a]	1.067[a]	0.826[a]
Telecommunications					
Telecommunications	0.807[a]	0.00008[a]	1.111[a]	0.132	1.009[a]
Fixed Line Telecommunications	1.209[a]	-0.00005[a]	1.184[a]	0.283	0.681[a]
Mobile Telecommunications	0.777[a]	0.00055[a]	n/a	n/a	0.760[a]
Benchmark					
All Share	0.185[a]	0.00007[a]	0.598[a]	0.206[a]	0.694[a]
Mid Cap	0.177[a]	0.00000[a]	0.360[a]	0.04	0.215[a]
Small Cap	0.118[a]	0.00003	0.244[a]	0.042[a]	0.057[a]
Secondary Markets					
ALT X	0.251[a]	-0.00039[a]	n/a	n/a	0.463[a]

Source: Author's own estimates

Notes: [a,b,c] implies coefficient is significant at 1%, 5% and 10% respectively.