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Abstract: This paper explores the relevance of ARCH-type models in explaining stock return dynamics on the JSE. Although the evidence suggests that volatility is prevalent on this market, it is establish ed that the effects of shocks on volatility are symmetric, and that volatility is not a commonly priced factor. Hence, the standard GARCH(1,1) model provides the best description of return dynamics relative to its complex augmentations. Further, the model significantly, but less than fully, accounts for the observed non-linearities in the series.

1. Introduction

In prior work (Mangani, 2005), we provided evidence on stylised statistical properties of stock prices and returns using data from the JSE Securities Exchange of South Africa (hereafter, JSE). Specifically, it was shown that although JSE logarithmic stock prices were non-stationary processes, continuously compounded returns did not seem to contain a unit root. Secondly, the distributions of returns on the market were not consistent with normality, and showed very strong evidence of leptokurtosis as well as excess skewness. Finally, the distributions showed strong departures from the assumption of being independently and identically distributed (iid), implying that stochastic or deterministic non-linearities could characterise the return generating process. These results pointed to the possibility that the parameters of the model governing the return generating process on the JSE might not be constant over time, but rather dynamic. Consequently, static (unconditional) and iid-based asset pricing investigations, which dominated most work conducted on the JSE, could be improved upon by recasting them to a dynamic framework. The autoregressive conditional heteroscedasticity (ARCH) type of models, which assume that the dynamical behaviour is characterised by a time-dependent variance, provide one possible such framework.

This paper, therefore, explores whether ARCH-type models could be used to explain stock return dynamics on the JSE. The motivation for this investigation is the common observation

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documented in the literature that, even when the return series are themselves linearly unpredictable, their squares usually exhibit some linear dependencies over time. This observation provides evidence that the variance of return (i.e., risk) is not constant over time, but exhibits temporal dependence and predictability (Mandelbrot, 1963). The key implication of this observation is that the conditional variance (i.e., volatility) of return, rather than the unconditional variance, is an important determinant in the investment decision-making process.

The class of ARCH-type models that could be explored to investigate the risk-return dynamics on the JSE is wide and growing, but this investigation was guided by the desire to establish (a) whether volatility was priced; (b) whether there existed volatility asymmetry; i.e., whether positive and negative shocks impacted on volatility differently; and (c) whether an ARCH-type model could account for non-linearities in the JSE returns.

Most previous studies addressing this subject have focused on very well-developed markets. Although work has been done in other emerging markets as well, hardly any such investigations are documented for the JSE. The present study seeks to address this gap.

The rest of this paper is organised as follows. Section 2 provides a brief overview of ARCH-type models, focusing on the models tested in the present study, and briefly reviews the literature. Section 3 describes the methodologies followed, while the results of the investigation are presented and discussed in Section 4. Section 5 summarises and concludes the paper.

2. Theoretical Framework and the Literature

The theoretical framework for modelling volatility and investigating its relationship with returns is usually traced to the original ARCH model developed by Engel (1982). Engel's ARCH model for returns recognises that there is a distinction between the unconditional second moment (i.e., variance) and conditional second moment (i.e., volatility) of the return series, in the sense that the latter can change over time even if its corresponding variance measure is homoscedastic. Therefore, in order to capture this time-variability, the ARCH framework imposes an autoregressive structure on the conditional second moment. Thus, if R_t denotes linearly unpredictable (either uncorrelated or linearly filtered) continuously compounded return in period t for a given security, and if a structural relationship is not assumed, R_t could be modelled as:

$$R_t = \alpha + \mu_t, \qquad (1)$$

$$\mu_t | \Omega_{t-1} \sim N(0, h_t), \quad (2)$$

$$h_t = \phi + \sum_{i=1}^{q} \lambda_i \mu_{t-i}^2 . \quad (3)$$

(1) gives the mean (expected) return equation, and shows that the expected return does not differ from its long-run average value, α, except by a random error term. (2) states that, conditional upon the set of information, denoted Ω_{t-1}, available in the preceding period, the error term is normally distributed with a mean of zero and a conditionally heteroscedastic variance, h_t. The error term is also serially uncorrelated by definition. The normality assumption could be relaxed in favour of more realistic distributions for μ_t, most commonly Student's t-distribution. Finally, by noting that $h_t = E(\mu_t^2 | \Omega_{t-1})$, (3) clearly models volatility as an AR(q) process, where the regressors denote shocks that impact on volatility. Together, (1) to (3) describe the standard ARCH(q) model, which has been found successful in describing the dynamics of various macroeconomic and financial variables. Among other applications of the model, see Engle and Kraft (1983) and Coulson and Robins (1985) on inflation, Weiss (1984) on macroeconomic variables, and Domowitz and Hakkio (1985) on foreign exchange markets.

Bollerslev (1986) observed that, in order to avoid a violation of the non-negativity constraints in view of the long memory typically found in empirical work, the original ARCH model requires that an arbitrary, and usually long, linear declining lag structure be imposed in the conditional variance equation. The result is that the value of q can usually not be small. In order to permit a parsimonious description of the process, he introduced the generalised ARCH (GARCH) model which extends (3) by including p lagged conditional variance terms as extra regressors. The p terms are commonly referred to as GARCH terms while the q terms retain their description as ARCH terms in this formulation. The volatility equation in the GARCH(p,q) model, therefore, becomes:

$$h_t = \phi + \sum_{i=1}^{q} \lambda_i \mu_{t-i}^2 + \sum_{j=1}^{p} \theta_j h_{t-j} . \quad (4)$$

The parsimony achievable through the use of the GARCH model implies that the dynamics of h_t that would best be described by a high-order ARCH process could just as well, and sometimes even better, be described by a low-order GARCH process. Therefore, although higher order GARCH models are preferred in some studies (e.g., Mills, 1999; Yu, 2002), the GARCH(1,1) process has demonstrated adequacy in modelling many time series. Note that the ARCH model is nested in the GARCH model by setting $p = 0$, while $p = q = 0$ implies that the variance is a white noise process. Further, the quantity $\sum \lambda_i + \sum \theta_j$ measures the persistence of volatility. If $\sum \lambda_i + \sum \theta_j = 1$, then shocks on volatility die off very slowly (an integrated GARCH - IGARCH process). The formulation of the GARCH model assumes that $\sum \lambda_i + \sum \theta_j < 1$ and, in most empirical applications, it is the presence of near-integrated GARCH processes that have been established (Bollerslev, 1987; Baillie & Bollerslev, 1989). Finally, by expressing (4) in terms of the squared errors, we have:

$$\mu_t^2 = \phi + \sum_{i=1}^{q} \lambda_i \mu_{t-i}^2 + \sum_{j=1}^{p} \theta_j \mu_{t-j}^2 + \sum_{j=1}^{p} \theta_j \varepsilon_{t-j} + \varepsilon_t \, , \qquad (5)$$

where ε_t is uncorrelated with zero mean. This conditional variance equation may also be expressed as an ARMA(m, p) process, where $m = \max\{p, q\}$.

Both of the foregoing ARCH-type models assume that positive and negative shocks of equal magnitude impact on volatility similarly. Nelson (1991), Glosten, Jaganathan and Runkle (1993), and Zakoian (1994) suggested formulations that are useful in modelling the differential impact of positive and negative shocks, a phenomenon called volatility asymmetry.

Nelson (1991) proposed a logarithmic conditional variance model in order to achieve exponential leverage effects, and to allow the model's coefficients to become negative without the variance itself becoming negative. Moreover, standardised lagged errors, as well as their moduli, enter the volatility equation as extra regressors, in order to allow for differential effects of positive and negative shocks. The volatility equation in the resulting exponential GARCH (EGARCH) model of order (p, q) model is, therefore:

$$\ln h_t = \phi + \sum_{i=1}^{q} \left(\lambda_i \frac{|\mu_{t-i}|}{\sqrt{h_{t-i}}} + \gamma_i \frac{\mu_{t-i}}{\sqrt{h_{t-i}}} \right) + \sum_{j=1}^{p} \theta_j \ln h_{t-j} \, , \qquad (6)$$

where γ_i are the leverage effect terms. A leverage effect is said to exist if $\sum \gamma_i > 0$, and asymmetric volatility is established if $\sum \gamma_i \neq 0$.

A simpler approach to modelling asymmetric effects on volatility is to introduce a dummy variable, say D_t, into the conditional variance equation. Specifically, D_t assumes a value of unity for bad news (i.e., $D_t = 1$ if $\mu_t < 0$), and a value of zero otherwise. This yields the Dummy GARCH (DGARCH) model proposed by Glosten *et al* (1993) (also called the GJR model) whose conditional variance equation is of the form:

$$h_t = \phi + \sum_{i=1}^{q} \lambda_i \mu_{t-i}^2 + \gamma D_{t-1} \mu_{t-1}^2 + \sum_{j}^{p} \theta_j h_{t-j} . \qquad (7)$$

In (7) the impact of good news on volatility is $\sum \lambda_i$, while that of bad news is $\sum \lambda_i + \gamma$. As in the EGARCH model, a leverage effect exists if $\gamma > 0$, and the news effects are asymmetric if $\gamma \neq 0$. Apart from its simplicity and the relative ease of interpretability of its parameter estimates, this formulation has been found useful in modelling volatility spillover effects from other markets (see Bae and Cheung, 1993, in Blake, 2000). Zakoian's (1994) formulation is not a significant departure from the GJR model. For compactness of notation, we shall refer to the class of asymmetric volatility models as AGARCH models.

The application of AGARCH models to data from various markets has produced conflicting conclusions. For instance, significant leverage effects were documented by Glosten *et al* (1993) for the US market, and by Siourounis (2002) for the Athens Stock Exchange, while Kasch-Haroutounian and Price (2001) found weak evidence in four emerging markets of Central Europe. Solibakke (2001) noted that asymmetric volatility was more significant in well traded than in thinly traded stocks in the Norwegian market.

Although the above models are useful in describing stochastic non-linear dynamics, they do not explain explicitly the relationship between volatility and the expected return on an asset. In order to address the central question of pricing risk, ARCH-in-mean or the GARCH-in-mean models were proposed by Engel, Lilien and Robins (1987) and Bollerslev, Engel and Wooldridge (1988). These formulations introduce the conditional variance (or the conditional standard deviation) as an extra regressor in the mean equation. If

R_t denotes uncorrelated (but not necessarily linearly-filtered) return series, then (1) may be modified to:

$$R_t = \alpha + \beta h_t + \mu_t \text{, or} \quad (8)$$

$$R_t = \alpha + \beta\sqrt{h_t} + \mu_t . \quad (8')$$

In (8) or (8'), α may be comparable to the rate of return on a risk-free asset, while β is the price of risk. The quantity of risk is estimated by the conditional variance or the conditional standard deviation. For the purpose of estimation, (8) and (8') assume that the return series are uncorrelated. If the series exhibits correlation, then the two-stage procedure of fitting the model on already linearly filtered data would not yield consistent estimators. Instead, the mean equation would be estimated as an autoregression (Brock *et al*, 1993:101). Finally, it is straightforward to see that when volatility is modelled as AGARCH (i.e., DGARCH or EGARCH) and the conditional variance (or standard deviation) term is also included in the mean equation, we obtain AGARCH-in-mean (AGARCH-M) models (i.e., DGARCH-M or EGARCH-M processes).

In recent applications of ARCH-type models to financial data, the GARCH-M and AGARCH-M processes are probably the most frequently used, and have been found to provide conflicting but generally unsuccessful results regarding the pricing of volatility. Specifically, the results from emerging markets have not been particularly above board. For instance, Alles and Murray (2001) found that the GARCH-M model was unsuitable for Irish equity markets, while Poshakwale and Murinde (2001) found that volatility was not priced in the stock markets of Poland and Hungary. These results are in agreement with those documented by Solibakke (2002) for the thinly traded Norwegian equity market. A similarly weak relation between returns and volatility was documented by Baillie and DeGennaro (1990) for the US market, and by Poon and Taylor (1992) for the UK market, but support for a negative relation between the two was provided by Glosten *et al* (1993) within the US environment.

Many other ARCH-type variants with equally witty acronyms have been proposed in the literature to capture various types of dynamics. An important extension, which nests most of the ARCH-type models, was made by Ding, Granger and Engle (1993), who recognised that if the distribution of the return series' error was non-normal, then moments different from the second could best describe the dynamics. Finally, extensions of the ARCH-type models to multivariate frameworks, as well as to models that could explain deterministic chaos, have been accomplished (e.g., Engel & Kroner, 1995). Thus, it is not possible to provide an exhaustive account in this very dynamic field within the context of this overview.

Although the importance of understanding the risk profiles of emerging capital markets is well-documented (Siourounis, 2002), the fact that very limited work in this area is reported for emerging markets is equally acknowledged (Kasch-Haroutounian & Price, 2001). One notable feature of the emerging markets literature on the relevance of ARCH-type models is its surge over the last few years. The models' increasing popularity appears to be premised on the fact that most of the emerging market studies seem to find them potentially capable of describing the unique features of the risk-return relationships that characterise such markets. But of more relevance to this study is the discernible absence, in the emerging markets literature, of work on the JSE and other African stock markets, of which the JSE is the most dominant and active. The present study attempts to fill this gap.

3. Research Methodologies

3.1 Sampling and Data

The choice of sample and study period was based on two major considerations. The first consideration was the trade-off between a long study period and a reasonably large number of securities to be included in the sample. The second consideration was based on the fact that on 24 June 2002, the JSE implemented the FTSE global classification system, and introduced the free float criterion which recognises that equity held for control purposes does not trade. These developments resulted in major changes to JSE sectors, the most notable being a significant decline in the number of stocks constituting the JSE All Share index from over four hundred and fifty to only one hundred and sixty as at 4 June 2002. Therefore, by studying only a few appropriately selected companies in the new All Share index, it became possible to capture a significant proportion of the truly trading segment of the JSE. On account of these considerations, this study randomly sampled forty-four stocks in the new All Share index for which continuous data were available since February 1973.

The forty-four stocks constituting the study sample are shown in Appendix 1. In addition to capturing as much as 46 percent of the FTSE/JSE All Share index, the selected stocks were fairly well distributed across the Safex indices. Specifically, at the time, the sample captured over 48 percent of the Top 40 index, and about 52 percent of the Resi index. Further, the sample respectively captured about 48 percent, 38 percent and 43 percent of the Indi, Fini and

Findi indices. Note that, on account of the free float criterion, five of the stocks in the final sample had a zero weighting in the indices.

In addition to the individual stocks, two stock portfolios were used to capture the aggregate behaviour of the market. The first was the new JSE All Share index whose data were spliced back to 1983. This is denoted ALSI in the ensuing analysis. Further, we constructed an equally weighted portfolio of the forty-four stocks described above, denoted PORT hereafter. Because ALSI is dominated by resources stocks, the use of the equally-weighted portfolio provided a measure of aggregate market dynamics that was not significantly influenced by the dynamics of the resources stocks.

The new JSE classification system partly provides a solution to the problems associated with non-synchronous trading and non-trading. Specifically, the Ground Rules that govern the FTSE/JSE Africa Index Series make a provision to ensure that illiquid securities will be excluded from the All Share index (see FTSE 2003a, Ground Rule 4.10). However, it is noted that our data could still exhibit some thin trading, particularly since they extended back to the 1970s. In the literature, it is recognised that a major effect of non-synchronous trading is to induce spurious autocorrelation (Atchison, Butler & Simonds, 1987), necessitating that corrective measures be employed to purify the data of linear dependencies. The present study applied such measures as discussed subsequently.

The primary data used in this analysis were weekly close prices for each of the individual stocks and portfolios. The study period extended from 23 February 1973 to 5 April 2002 for the individual stocks and PORT, and from 23 December 1983 to 5 April 2002 for ALSI. For the period up to 22 September 2001, close price data on the individual stocks were obtained from an online database maintained by the Statistical Sciences Department of the University of Cape Town, while the rest of the data up to April 2002 were obtained from the Inet-Bridge online database. The close price data on ALSI, spliced back to 1983, were also sourced from the Inet-Bridge.

Using the close prices, continuously compounded returns at each time t, denoted R_t, were computed as first differences of logarithmic price. After the necessary computational data adjustments, the final sample had 1519 observations of price and return series for each individual stock and PORT, and 954 observations for ALSI.

3.2 Volatility Clustering

In order to contextualise the relevance of ARCH-type models, the following exploratory analysis of the data was invoked. Initially, an autoregressive structure was used to filter linear dependencies in each of the raw return series, if their presence could be detected. The autoregressive structures in the correlated return series were chosen such as to filter autocorrelation of up to the tenth order, as confirmed by the Breusch-Godfrey serial correlation LM test. The series, therefore, represented linearly unpredictable returns. However, we further examined the ACFs and PACFs, as well as the Ljung-Box Q-statistics for the squares of each of these linearly independent return series. The full results of this investigation, available from the author upon request, showed strong evidence of positive linear dependencies in the squares of unpredictable returns. In Figure 1, stock TNT is randomly used to illustrate the typical pattern exhibited by most of the stocks and portfolios in the sample, and the cyclicality in volatility is quite clear. For most such series, the ACFs at lag one were significant, and the PACFs showed that autocorrelations at subsequent lags generally contributed relatively less to the patterns of the linear dependence. For most of the series, the Q-statistics were significant at 1 percent at very low lags. These findings entailed volatility clustering, and supported the use of ARCH-type models to describe return dynamics on the JSE.

3.2 Model Estimation, Identification, and Appraisal

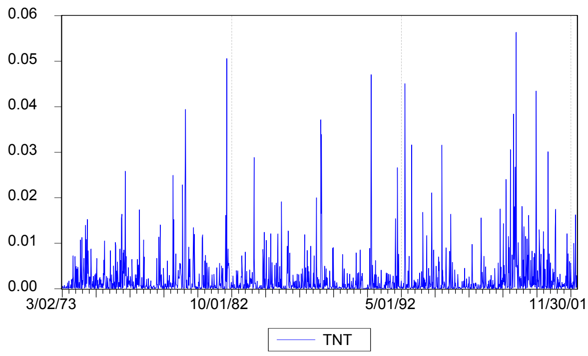
Engel (1982), and Sumel and Engel (1994), among others, argued that the ARCH model was capable of accounting for volatility clustering in uncorrelated error terms with leptokurtic distributions[1]. In order to capture leptokurtosis, the normality assumption in (2) is sometimes relaxed in favour of fat-tailed alternatives, usually the Student's t-density. This modification is particularly useful when the maximum likelihood parameters of the variance equation are estimated using the traditional BHHH algorithm due to Berndt, Hall, Hall and Hausman (1974). This notwithstanding, ARCH-type models are generally estimated using the maximum likelihood technique under the assumption that the error terms are conditionally normally distributed, so that the model's parameter estimates are asymptotically efficient. Moreover, even if the error terms are not normally distributed, the estimates of the model are still consistent under quasi-maximum likelihood (QML) assumptions. In this study, in order to improve the convergence rate of the iterative process, the maximum likelihood

[1] See also Baillie and DeGennaro, 1990, as well as Poon and Taylor, 1992.

estimation technique used employed the Marquardt algorithm. Throughout, robust standard errors (and hence robust z-statistics) were obtained by utilising the QML method as proposed by Bollerslev and Wooldridge (1992).

Figure 1 – Volatility clustering

This figure shows plots of squared linearly unpredictable returns on TNT against time.



The general procedure followed to address the key objectives of this paper was to identify the appropriate ARCH-type model for each of the market aggregates and individual stocks. Rather than impose the GARCH(1,1) specification on the basis of its popularity, the values of p and q were empirically confirmed in the study. First, note that the patterns of the ACFs and Q-statistics of squared linearly unpredictable returns already discussed were comparable with those for squared residual estimates from an OLS estimation of (1), where R_t denoted linearly unpredictable returns. Although these results apparently suggested the GARCH(1,1) model for most of the series, there were some possible indications of relatively higher order GARCH processes. Therefore, following Solibakke (2001), ARMA(1,1) ARMA(1,2), ARMA(2,1) and ARMA(2,2) models were fitted to the squared residual estimates themselves[2], and the optimal lag structure was initially chosen on the basis of the Akaike and Schwarz information criteria. The use of the information-based criteria (denoted AIC and SIC, respectively) was supported by the fact that they usually suggest parsimonious models, which are preferred in the GARCH procedure. The ARMA model that yielded

[2] In the case of return series for which serial correlation was filtered through an autoregression, this was equivalent to fitting an ARMA model on the squared unpredictable returns.

the lowest values of the two statistics was chosen for each stock. It is not unusual for the two statistics to suggest the same models, but where they yielded conflicting results, model selection was based on the relatively more conservative SIC.

The SIC and AIC statistics are omitted in this paper to conserve space, but are available from the author upon request. Our examination of these statistics confirmed the documented popularity of the GARCH(1,1) model, which was clearly suggested for thirty-two of the forty-four individual stocks, in view of its direct analogy to the ARMA(1,1) model of squared residual estimates. In addition, there was some support for the GARCH(2,1) model, which was apparently appropriate in modelling the dynamics of both aggregates as well as ten individual stocks. Finally, both the GARCH(1,2) and the GARCH(2,2) processes could each be used to describe volatility in one stock only, namely SBK and JNC, respectively. It is also worth mentioning that almost two-thirds of the final GARCH specifications were mutually suggested by the SIC and the AIC.

In order to validate the findings of the preceding analysis as far as the choice of higher order GARCH formulations was concerned, we estimated the suggested models as well as the GARCH(1,1) model for the two aggregates and twelve stocks involved. The estimation results, also available from the author upon request, clearly suggested that the GARCH(1,1) specification would be a significant improvement in modelling volatility for these series. While only six of the twenty-seven GARCH coefficients were statistically significant in the higher order models at 5 percent, all such coefficients were very significantly positive in the low-order specification. In addition, the low-order model yielded improvements in the statistical significance of ARCH coefficients for quite a few securities, although there were some declines in the log likelihood functions for PORT and eight stocks. Further, only three of the fifteen higher order parameters were themselves significant. These results generally suggested that the GARCH(1,1) model was the most appropriate for the JSE.

Augmentations of the model to capture asymmetric volatility effects and the pricing of volatility was a straightforward exercise. As presented in Table 1, an examination of the log likelihood functions generated by the various models provided *prima facie* justification for such extensions, since the extensions yielded higher log likelihood functions than those derived from the standard GARCH model, except for stocks AGL and WLO. It should be noted that, even after a great deal of re-specification efforts for the mean equation, the parameters of the in-mean models could not converge in the case of seven stocks (i.e., AGL, ASR, AVI, BAW, DEL, DUR and MLB). Further, note that on the basis of the log likelihood function, the DGARCH-M model could be most preferred among the four models, since it was suggested for sixteen of the thirty-seven stocks that encountered no parameter convergence problems during model estimation, as well as the market aggregates.

A specific-to-general modelling procedure was pursued in the investigation. Thus, the suggested GARCH models were first fitted to each of the series, and these were subsequently generalised in an attempt to capture some of the salient issues discussed in the previous section. In order to investigate the presence of asymmetric effects of shocks on volatility, both the EGARCH and the DGARCH models were attempted. Following Mills (1999), the choice between EGARCH and DGARCH was initially based on simple comparisons of the values of log-likelihood functions generated by the models for each series, a higher value being preferred. Table 1 shows that the DGRACH model was suggested for thirty securities, while the remaining sixteen (including the aggregates) could be modelled as EGARCH processes. In an attempt to substantiate this observation, a comparison between the estimation results of the EGARCH and DGARCH models for the sixteen securities was made, and the estimation results are summarised in Table 2.

Focusing on the statistical significance of the ARCH and GARCH terms in Table 2, it was noted that the EGARCH model performed at least as well as the DGARCH model for both aggregates as well as eleven of the fourteen stocks. The notable exceptions were ASR, MBL and TRE, where the DGARCH model was somewhat a better fit. More importantly, it was further noted that the coefficient for the leverage effect term was negative in the EGARCH model for virtually all but one stock (i.e., BAW), while all but two stocks (i.e., BAW and MLB) and both aggregates yielded positive leverage effect coefficients in the DGARCH model. Since a positive coefficient was consistent with *a priori* expectations, there was no compelling theoretical reason to suggest that the EGARCH model was a better fit. Hence, we chose to model all the securities as DGARCH processes.

Table 1 – Log likelihood functions of the ARCH-type models

This table presents the log likelihood functions for the various ARCH-type models fitted to the return series. ♦ identifies the log likelihood function-preferred model among all models. The log likelihood function for the preferred AGARCH model is grey-shaded. NC indicates parameter non-convergence.

(a) Stock portfolios

Portfolio	*GARCH*	*DGARCH*	*EGARCH*	*GARCH-M*	*DGARCH-M*
ALSI	2093.781	2094.239	2096.955	2096.569	2096.977♦
PORT	3774.011	3776.796	3777.181	3775.024	3777.510♦

(b) Individual stocks

Security	*GARCH*	*DGARCH*	*EGARCH*	*GARCH-M*	*DGARCH-M*
AFE	2424.357	2424.388	2410.140	2425.127	2426.040♦
AFX	2652.717	2653.400	2635.509	2653.012	2654.544♦
AGL	2265.717♦	2174.754	2202.770	NC	NC
ALT	2477.569	2478.599♦	2425.509	2473.249	2442.856
ANG	2232.506	2233.111♦	2232.187	2231.545	2232.259
ASR	1473.714	1481.040	1550.606♦	NC	NC
AVI	2511.434	2511.666♦	2400.071	NC	NC
BAW	2526.944	2543.911	2553.706♦	NC	NC
BVT	2592.865	2608.105♦	2548.039	2591.797	2606.626
CHE	2699.758	2713.322	2667.800	2701.811	2718.101♦
CRH	1733.839	1734.656♦	1701.928	1733.462	1734.325
CTP	2364.497	2376.305	2376.675	2366.893	2377.737♦
DEL	2351.470	2362.415♦	2202.939	NC	NC
DUR	1572.637	1572.746	1571.002	1579.237♦	NC
ECO	2681.322	2686.619♦	2680.154	2678.268	2684.024
ELH	2437.374	2449.065	2419.634	2438.810	2449.819♦
FOS	2548.144	2557.855	2541.984	2548.977	2558.890♦
GMF	2322.692	2322.953♦	2304.764	2321.013	2321.025
HAR	1962.282	1963.745	1963.038	1964.117	1965.997♦
HLH	2391.601	2392.184	2398.420♦	2383.253	2384.087
HVL	2289.434	2291.965	2293.894♦	2287.854	2288.530
IMP	2158.371	2162.014♦	2160.772	2156.852	2160.741
JCM	2123.012	2124.983	2036.970	2155.436	2163.069♦
JNC	1853.832	1862.793	1320.556	2029.186	2042.138♦
LGL	2671.537	2678.816	2617.860	2672.847	2679.458♦
MAF	2439.468	2528.479♦	1989.186	2406.177	2500.892
MLB	2030.714	2038.777	2100.796♦	NC	NC
NED	2635.625	2648.688	2651.377♦	2635.679	2649.106
NPK	2751.847	2752.966	2761.470♦	2750.201	2752.885
OCE	2526.558	2526.721	2537.319♦	2528.553	2528.579
PAM	2513.450	2516.898	2512.783	2514.367	2517.623♦

PIK	2312.804	2315.272	2300.891	2315.308	2315.526♦
PPC	2889.467	2890.253	2901.400♦	2890.260	2890.846
REM	2175.333	2186.647	2177.824	2224.578	2238.670♦
RLO	2415.841	2416.101♦	2412.714	2413.922	2413.983
SAB	2682.258	2682.727	2662.638	2686.976	2686.989♦
SAP	2346.042	2347.170	2352.433♦	2347.279	2348.555
SBK	2738.245	2738.435	2731.274	2745.576	2745.767♦
TBS	2745.423	2754.858♦	2703.367	2744.775	2754.464
TNT	2511.125	2513.876	2519.795♦	2509.110	2511.965
TRE	1337.815	1344.081	1434.371♦	1387.529	1328.187
VNF	2219.484	2222.408♦	2184.496	2221.226	2221.727
WAR	1794.836	1795.882	1794.778	1795.687	1796.637♦
WLO	2522.632♦	2514.562	2512.309	2514.530	2514.559

Table 2 – ML estimation of AGARCH models: selected securities

*This table shows the maximum likelihood estimates (with robust z-statistics in parentheses) of the DGARCH and EGARCH models for the sixteen securities for which the EGARCH model was preferred to the DGARCH model on the basis of the log likelihood function (see Table 4.4). For both models, the conditional mean equation was (4.1). The conditional variance equations were (4.6) for EGARCH and (4.7) for DGARCH. * denotes statistical significance at 1%, while ** denotes significance at 5%.*

(a) Stock portfolios

Portfolio	***Model***	α	ϕ	λ_1	γ	θ_1
	DGARCH	0.000	0.000	0.102	0.041	0.786
		(0.320)	(1.806)	(1.567)	(0.544)	(10.363)*
	EGARCH	0.000	-0.000	0.248	-0.051	0.897
ALSI		(0.350)	(-2.52)**	(3.755)*	(-1.167)	(18.695)*
	DGARCH	0.000	0.000	0.053	0.060	0.857
		(0.411)	(3.759)*	(2.152)**	(1.624)	(31.952)*
	EGARCH	0.000	-0.000	0.212	-0.051	0.917
PORT		(0.157)	(-3.97)*	(3.855)*	(-1.71)	(38.880)*

(b) Individual stocks

Security	***Model***	α	ϕ	λ_1	γ	θ_1
AGL	DGARCH EGARCH	0.006 (2.160)** 0.004 (2.433)**	0.002 (6.999)* -5.958 (-6.308)*	0.049 (0.751) 0.585 (3.560)*	1.461 (0.867) -0.357 (-1.292)	0.006 (0.375) 0.047 (0.248)
ASR	DGARCH EGARCH	-0.000 (- 0.269) 0.000 (0.000)	0.005 (1.097) -4.876 (-0.900)	-0.053 (- 1.98)** -0.268 (- 0.579)	0.052 (1.982)** -0.188 (-0.608)	0.612 (1.126) 0.010 (0.008)
BAW	DGARCH EGARCH	-0.000 (-0.044) -0.000 (-0.021)	0.000 (4.301)* -0.524 (-4.013)*	0.228 (1.353) 0.214 (2.666)*	-0.167 (-0.841) 0.080 (0.703)	0.814 (24.476)* 0.940 (56.198)*

CTP	DGARCH EGARCH	0.003 (2.532)** 0.005 (4.021)*	0.000 (1.754) -0.345 (-2.26)**	0.025 (0.992) 0.151 (2.333)**	0.068 (1.979)** -0.092 (-3.434)*	0.923 (23.549)* 0.958 (48.102)*
HLH	DGARCH EGARCH	0.002 (2.426)** 0.003 (2.552)**	0.000 (2.454)** -0.421 (-2.65)**	0.085 (1.883) 0.208 (2.506)**	0.024 (0.725) -0.045 (-1.510)	0.894 (29.203)* 0.952 (47.083)*
HVL	DGARCH EGARCH	-0.000 (-0.338) -0.001 (-0.832)	0.000 (1.413) -0.011 (-2.11)**	-0.001 (-0.089) 0.211 (3.934)*	0.029 (2.477)** -0.015 (-0.416)	0.979 (88.855)* 0.852 (11.330)*
MLB	DGARCH EGARCH	0.001 (0.442) 0.001 (1.049)	0.002 (1.701) -4.692 (-1.93)	0.073 (1.527) 0.155 (1.423)	-0.077 (-1.607) -0.120 (-1.285)	0.568 (2.446)** 0.180 (0.384)
NED	DGARCH EGARCH	0.003 (2.758)* 0.003 (2.808)*	0.000 (3.103)* -0.309 (-3.490)*	0.013 (0.702) 0.108 (2.949)*	0.106 (3.118)* -0.080 (-3.645)*	0.874 (27.401)* 0.964 (81.731)*
NPK	DGARCH EGARCH	0.003 (2.881)* 0.003 (3.189)*	0.000 (2.740)* -0.333 (-3.256)*	0.036 (2.102)** 0.131 (3.722)*	0.032 (1.314) -0.034 (-1.575)	0.914 (41.473)* 0.963 (70.706)*
OCE	DGARCH EGARCH	0.003 (2.954)* 0.003 (2.807)*	0.000 (1.277) -0.353 (-2.12)**	0.048 (2.408)** 0.130 (3.348)*	-0.002 (-0.038) -0.006 (-0.103)	0.928 (24.469)* 0.956 (41.206)*
PPC	DGARCH EGARCH	0.000 (0.191) -0.000 (-0.177)	0.000 (1.741) -0.850 (-2.15)**	0.029 (1.730) 0.084 (2.955)*	0.017 (0.854) -0.014 (-0.575)	0.936 (39.675)* 0.981 (87.930)*
SAP	DGARCH EGARCH	0.003 (2.084)** 0.003 (2.371)**	0.000 (1.646) -0.109 (-2.578)*	0.031 (2.498)** 0.073 (3.353)*	0.019 (0.931) -0.034 (-2.450)*	0.947 (63.035)* 0.991 (162.82)*
TNT	DGARCH EGARCH	0.002 (2.133)** 0.002 (2.019)**	0.000 (3.041)* -0.784 (-3.284)*	0.062 (1.966)** 0.205 (3.729)*	0.059 (1.195) -0.057 (-1.401)	0.816 (16.958)* 0.896 (25.618)*
TRE	DGARCH EGARCH	0.004 (1.721) -0.000 (-0.662)	0.006 (1.721) -4.530 (-4.528)*	-0.003 (-3.217)* -0.101 (-0.757)	-0.000 (-1.87) -0.372 (-1.96)**	0.596 (1.884) 0.047 (0.311)

In order to investigate whether volatility was priced on the JSE, a conditional variance term was introduced in the mean equation, and the statistical significance of the associated coefficient, denoted β, was evaluated. Finally, a general AGARCH-M model was fitted to each of the series, in an attempt to capture all the effects simultaneously. Ward tests were then applied to investigate whether the leverage effect variable and the in-mean variable were jointly statistically significant. Under the null hypothesis that $\gamma = \beta = 0$, the Ward test statistic has a χ_2^2 distribution.

An additional comparison made across the models was to assess the degree of persistence implied by each model. Noting the nonnestedness feature of the models, we adopted the procedure of Glosten *et al* (1993), where the following first order autoregressive scheme:

$$h_t = \psi + \rho h_{t-1} + \nu_t, \qquad (9)$$

was fitted to the estimated volatility series from each model, and the magnitude and significance of the autoregressive parameter were assessed and compared across models. In addition, the volatility persistence implied by the standard GARCH model was calculated as a simple summation of the ARCH and GARCH terms, and appraised.

Finally, we were particularly interested in establishing whether the successful model for each series was capable of explaining the observed non-linearities in the data. Therefore, we applied the linearity test due to Brock, Dechert and Scheinkman (1987) on the standardised residuals from the model. A summarised description of the so-called BDS test is in Mangani (2005) where an application using the same data set of JSE returns is illustrated. The test was, therefore, herein applied as therein described[3]. However, because the distribution of such standardised residuals is known to be inconsistent with the standard normal, the test was conducted using the EViews 4.0 software, rather than the LeBaron (1991) programme used in the prior investigation. The use of EViews 4.0 facilitated the bootstrapping of probability values for accepting the null hypothesis of linearity, which was done using 1000 iterative repetitions. If the model was capable of capturing all the non-linearities, the test should not reject the iid null hypothesis when thus applied. In this context, the BDS test was used as a test for correct model specification.

Two points ought to be mentioned regarding the ensuing analysis. Firstly, it is trivial, yet of necessity, to note that a parameter estimate that is statistically significant at 10 percent is equivalently significantly positive or negative at the 5 percent level. As such, we evaluated two-tail statistical significance at 10 percent in the succeeding analysis, to achieve the aforesaid 5 percent one-tail equivalence. Secondly, since no strict structural model was assumed for the mean equation, there was no motivation for a statistical evaluation of this equation, except in terms of the worth of the in-mean variable.

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[3] In particular, the choice of values for embedding dimension and closeness gauge made in Chapter 3 were maintained in this chapter, i.e., $m = 2,3,4,5$ and $l = 0.5\sigma, 1.0\sigma, 1.5\sigma$, where σ was the standard deviation of the data.

In the ensuing discussions, the estimation results for the two portfolios are contextually presented in this paper but, for want of space, only summaries are provided for the individual stocks. Interested readers may consult the author for the complete estimation results.

4. Main Results and Discussions

4.1 GARCH Model Estimation

For the results of estimating the GARCH(1,1) model, Table 3 refers. The results indicated that the standard GARCH process was a successful univariate model of volatility on the JSE. Firstly, the coefficient for the GARCH term, θ_1, was significantly positive in all but two cases (ASR and MLB), and remained positive but insignificant for those two stocks. In most cases, the level of significance was exceedingly high, implying strong evidence that volatility in the previous week sturdily explained current volatility. The estimated values for the coefficient were also quite high (generally close to, but less than unity). This had an implication for the structure of volatility persistence. We revert to this issue later.

Secondly, the ARCH term also yielded a commonly positive coefficient ($\lambda_1 > 0$ in forty-three of the forty-six cases), which was significant in forty instances. For three stocks (ASR, MLB and TRE), it is interesting to note that λ_1 was actually significantly negative, showing an inverse relationship between shocks and volatility. Although the estimated values for λ_1 in these three stocks were very low in absolute value terms, the effects of the term might not be ignored, particularly considering that the concerned stocks also yielded relatively low and practically insignificant estimates for θ_1. All in all, the empirical findings indicated that strong GARCH effects were apparent on the JSE, and that individual stock dynamics could be approximated well by the dynamics for the market aggregates.

Table 3 - GARCH model estimation results

*This table summarises the estimation results for the standard GARCH(1,1) model. The conditional mean and volatility equations are given by (1) and (4) above, respectively. In part (a), robust z-statistics are in parentheses, while *, ** and *** denote statistical significance at 1%, 5% and 10%, respectively In part (b), C in the first column is the estimated coefficient in the model, and could take any of the values indicated in the third column. For each such value, the stocks and numbers of stocks in the sample whose estimated value for C corresponded with that indicated in the third column are given in columns four and five, respectively.*

a) Stock Portfolios

Portfolio	α	ϕ	λ_1	θ_1	***Log L***
ALSI	0.000 (0.469)	0.000 (1.76)	0.124 (2.843)*	0.795 (11.26)*	2093.8
PORT	0.000 (0.860)	0.000 (3.388)*	0.090 (3.879)*	0.856 (29.37)*	3774.0

b) Individual Stocks

C	***Row***	***Value of C***	***Securities***	***No.***
α	#1	Positive	All stocks but those in Row #3	37
	#2	Significantly positive	AFX, ANG, CTP, GMF, HLH, JCM, NED, NPK, OCE, PIK, SAB, SAP, TNT	13
	#3	Negative	ALT, BAW, DUR, HAR, HVL MLB, REM,	7
	#4	Significantly negative	None	0
	#5	Not significant	All but those in Row #2	31
ϕ	#6	Positive	All stocks	44
	#7	Significantly positive	ANG, BAW, BVT, DUR, ECO, ELH, HAR, HLH, HVL, IMP, MAF, NED, NPK, PAM, PPC, REM, SBK, TBS, TNT, VNF, WAR	21
	#8	Negative	None	0
	#9	Significantly negative	None	0
	#10	Not significant	All stocks but those in Row #7	23
λ_1	#11	Positive	All stocks but those in Row #13	41
	#12	Significantly positive	All stocks but those in Row #13 and Row #15	35
	#13	Negative	ASR, MLB, TRE	3
	#14	Significantly negative	ASR, MLB, TRE	3
	#15	Not significant	AFE, ALT, JCM, MAF, REM, VNF	6
θ_1	#16	Positive	All stocks	44
	#17	Significantly positive	All stocks but those in Row #20	42
	#18	Negative	None	0
	#19	Significantly negative	None	0
	#20	Not significant	ASR, MLB	2

4.2 Dummy GARCH Model Estimation

In Table 4, a summary of the results of estimating the DGARCH model is presented. It was noted that the asymmetric effect term was positive for both portfolios and twenty-eight of the individual stocks, but significantly so for only nine stocks. For the said nine stocks, therefore, a negative shock apparently tended to increase volatility by more than a positive shock of similar magnitude (i.e., there were seemingly significant leverage effects). Although the remaining stocks showed that a negative shock could reduce volatility by more than a positive shock of equal magnitude ($\gamma < 0$), the parameter was only significant for two of the sixteen stocks involved. Therefore, the *prima facie* evidence was that asymmetric effects could be observed in one-quarter of the stocks under investigation, but not in any of the aggregates, and that most of these observed asymmetries were consistent with the supposition of a leverage effect. This observation notwithstanding, it was further noted that the ARCH term parameter became statistically insignificant in virtually all stocks that showed evidence of significant asymmetric effects. This could imply that the ARCH term and the asymmetric effect term were highly collinear, and hence that the significance of the asymmetric effect parameter was spurious. Collinearity also potentially spanned other stocks and ALSI, such that only twenty stocks and PORT had significant ARCH term coefficients in the DGARCH model, compared with thirty-eight stocks and both aggregates in the GARCH model. This led us to suspect that the asymmetric effect term was 'detrimental' to the estimation of the model, and to conclude that genuine asymmetric effects were not discernible on the market.

Except for the above observations, the results of fitting the DGARCH model were quite comparable with those of the standard GARCH specification. Specifically, the first order GARCH term was not affected by the inclusion of the asymmetric effect term. Since the 'detrimental' variable was clearly collinear with only one other variable, namely the ARCH term, its omission was deemed appropriate in improving parameter estimation, in the spirit of Frisch's confluence analysis (Koutsoyiannis, 1988).

4.3 GARCH-in-Mean Model Estimation

The results of estimating the GARCH-M model are presented in Table 5. As alluded to in subsection 4.1, convergence could not be achieved in the estimation of the parameters of the model for six stocks, namely AGL, ASR, AVI, BAW, DEL, and MLB, such that the analysis was based on the remaining forty assets. It will be noted from the table that the volatility coefficient in the mean equation was negative for PORT and twenty-seven of the stocks, but only significantly so for PORT and JNC. Further, only DUR and HAR among the individual stocks showed that volatility was positively priced in their return dynamics. For these, an increase in volatility was, on average, associated with higher expected returns. Since the general requirement for a priced factor is that it should be common across the stocks in the market, volatility could be perceived as representing idiosyncratic risk for the few assets where it was priced. This could suggest that volatility did not meet the criterion of a priced factor, and that we could look for JSE priced factors elsewhere. The behaviour of PORT in this model rendered suspicious the use of aggregates in determining the empirical nature of the risk-return relationship for stocks: the highly statistically significant return-dampening effect of volatility observed in PORT did not seem to be characteristic of individual stock dynamics, nor of the market index.

Table 4 - DGARCH model estimation results

This table provides a summary of the estimation results for the DGARCH model. The specific conditional mean and volatility equations are given by (1) and (7), respectively. Entries are as defined in Table 3.

(a) Stock portfolios

Portfolio	α	ϕ	λ_1	γ	θ_1
ALSI	0.000 (0.320)	0.000 (1.806)	0.102 (1.567)	0.041 (0.544)	0.786 (10.363)*
PORT	0.000 (0.411)	0.000 (3.759)*	0.053 (2.152)**	0.060 (1.624)	0.857 (31.952)*

(b) Individual Stocks

C	*Row*	*Value of C*	*Stocks*	*No.*
α	#1	Positive	All stocks but those in Row #3	34
	#2	Significantly positive	AFX, AGL, CTP, DEL, GMF, HLH, JCM, JNC, LGL, MAF, NED, NPK, OCE, PIK, SAB, SAP, TNT, TRE	18
	#3	Negative	ALT, ASR, BAW, BVT, CHE, CRH, DUR, HAR, HVL, REM	10
	#4	Significantly negative	None	0
	#5	Not significant	All stocks in Row #3 as well as AFE, ANG, AVI, ECO, ELH, FOS, IMP, MLB, PAM, PPC, RLO, SBK, TBS, VNF, WLO	25
ϕ	#6	Positive	All stocks	44
	#7	Significantly positive	AGL, ANG, BAW, BVT, CHE, CTP, DUR, ECO, ELH, HAR, HLH, IMP, MAF, MLB, NED, NPK, PAM, PPC, REM, SAP, SBK, TBS, TNT, TRE, WAR, WLO	21
	#8	Negative	None	0
	#9	Significantly negative	None	0
	#10	Not significant	All stocks but those in Row #7	23

λ_1	#11	Positive	All stocks but those in Row #13	41
	#12	Significantly positive	AFX, ANG, AVI, DEL, DUR, HAR, HLH, NPK, OCE, PAM, PPC, SAB, SAP, SBK, TNT, VNF, WAR, WLO	18
	#13	Negative	ASR, CHE, HVL, TRE	4
	#14	Significantly negative	ASR, TRE	2
	#15	Not significant	All stocks but those in Row #12 and Row #14	24
γ	#16	Positive	All stocks but those in Row #18	28
	#17	Significantly positive	ASR, BVT, CHE, CTP, ELH, HVL, LGL, NED, TBS,	9
	#18	Negative	AFE, ALT, BAW, DEL, DUR, GMF, JCM, JNC, MAF, MLB, OCE, REM, SBK, TRE, VNF, WLO	16
	#19	Significantly negative	TRE, VNF	2
	#20	Not significant	All stocks but those in Row #17 and Row #19	33
θ_1	#21	Positive	All stocks	44
	#22	Significantly positive	All stocks but those in Row #25	41
	#23	Negative	None	0
	#24	Significantly negative	None	0
	#25	Not significant	AGL, ASR, REM,	3

Except for the apparent lack of success of the GARCH-M model documented above, the model retained the desirable attributes of the standard GARCH process: generally significant ARCH and GARCH coefficients in the volatility equation. This contrasted sharply with the results obtained from the DGARCH process already discussed, and pointed to the possibility of reformulating the mean equation such as to provide a pricing relationship for stocks. One way by which this could be done is to introduce priced factors, which could be macroeconomic-based or otherwise, as extra regressors.

4.4 Dummy GARCH-in-Mean Model Estimation

Fitting the most general DGARCH-M process to the individual stock return series yielded the results reported in Table 6. As was the case with the GARCH-M model, convergence could not be achieved in the estimation of the parameters of the model for seven stocks. Therefore, the results of this analysis were based on the remaining thirty-nine assets. These results, summarized in Table 6, showed that the more general DGARCH-M model retained the combined weaknesses of both the DGARCH and GARCH-M models.

Table 5 – GARCH-M model estimation results

This table provides a summary of the estimation results for the GARCH-M model. For uncorrelated returns, the specific conditional mean and volatility equations are given by (8) and (4), respectively. For correlated returns, the mean equation included AR terms. Because of parameter non-convergence, six stocks (i.e., AGL, ASR, AVI, BAW, DEL, and MLB) were excluded from the analysis. Entries are as defined in Table 3.

(a) Stock portfolios

Portfolio	α	β	ϕ	λ_1	θ_1
ALSI	0.003 (1.949)***	0.064 (0.029)	0.000 (1.806)***	0.152 (2.734)*	0.765 (9.376)*
PORT	0.005 (3.870)*	-5.400 (-1.706)***	0.000 (3.631)*	0.117 (3.881)*	0.806 (21.781)*

(b) Individual stocks

C	*Row*	*Value of C*	*Stocks*	*No.*
α	#1	Positive	All stocks but those in Row #3	31
	#2	Significantly positive	AFX, HLH, ELH, JCM, JNC, LGL, MAF, REM, SAB, SBK, TBS, TNT, VNF	13
	#3	Negative	ANG, CRH, DUR, GMF, PAM, SAP, WAR	7
	#4	Significantly negative	DUR	1
	#5	Not significant	All stocks but those in Row #2 and in Row # 4	24
β	#6	Positive	ALT, ANG, BVT, CRH, CTP, DUR, GMF, HAR, HVL, PAM, PIK, SAP, WAR	13
	#7	Significantly positive	DUR, HAR	2
	#8	Negative	All stocks but those in Row #6	25
	#9	Significantly negative	JNC	1
	#10	Not significant	All stocks but those in Row #7 and Row #9	35
ϕ	#11	Positive	All stocks	38
	#12	Significantly positive	All stocks but those in Row #15	24
	#13	Negative	None	0
	#14	Significantly negative	None	0
	#15	Not significant	AFX, CRH, CTP, GMF, IMP, JNC, LGL, OCE, PIK, RLO, SAB, SAP, TRE, VNF	14
λ_1	#16	Positive	All stocks but that in Row #18	37
	#17	Significantly positive	All stocks but those in Row #18 and Row #20	33
	#18	Negative	TRE	1
	#19	Significantly negative	TRE	1
	#20	Not significant	GMF, MAF, REM, VNF,	4
	#21	Positive	All stocks	38

θ_1	#22	Significantly positive	All stocks	38
	#23	Negative	None	0
	#24	Significantly negative	None	0
	#25	Not significant	None	0

Table 6 – DGARCH-M model estimation results: summary of findings

This table provides a summary of the estimation results for the DGARCH-M model. For uncorrelated stock returns, the specific conditional mean and volatility equations are given by (8) and (7). For correlated returns, the mean equation included AR terms. Because of parameter non-convergence, seven stocks (i.e., AGL, ASR, AVI, BAW, DEL, DUR and MLB) were excluded from the analysis. Entries are as defined in Table 3.

(a) Stock portfolios

Portfolio	α	β	ϕ	λ_1	γ	θ_1
ALSI	0.003 (1.997)**	-0.211 (-0.097)	0.000 (1.890)***	0.130 (1.615)	0.044 (0.545)	0.755 (8.798)*
PORT	0.005 (3.732)*	-5.949 (-1.9)***	0.000 (3.960)*	0.082 (2.558)**	0.075 (1.745)***	0.792 (21.927)*

(b) Individual stocks

C	***Row***	***Value of C***	***Stocks***	***No.***
α	#1	Positive	All stocks but those in Row #3	26
	#2	Significantly positive	AFX, CTP, JCM, ELH, JCM, JNC, LGL, NED, OCE, REM, SAB, SBK, TNT, TRE, VNF	15
	#3	Negative	ALT, ANG, CHE, CRH, GMF, HAR, HVL, PAM, PIK, SAP, WAR	11
	#4	Significantly negative	HAR, REM, WAR	3
	#5	Not significant	All stocks but those in Row #2 and in Row # 4	19
β	#6	Positive	ALT, ANG, BVT, CHE, CRH, ECO, GMF, HAR, HVL, JCM, PAM, PIK, SAP, TBS, WAR	15
	#7	Significantly positive	HAR, WAR	2
	#8	Negative	All stocks but those in Row #6	22
	#9	Significantly negative	None	0
	#10	Not significant	All stocks but those in Row #7	35
ϕ	#11	Positive	All stocks	37
	#12	Significantly positive	All stocks but those in Row #15	22
	#13	Negative	None	0
	#14	Significantly negative	None	0
	#15	Not significant	AFX, CRH, FOS, GMF, IMP, JNC, MAF, LGL, PIK, RLO, SAP, VNF	12

λ_1	#16	Positive	All stocks but that in Row #18	36
	#17	Significantly positive	ANG, CTP, HAR, HLH, HVL, NKP, OCE, PAM, PPC, SAB, SAP, SBK, TNT, VNF, WAR, WLO	16
	#18	Negative	CHE	1
	#19	Significantly negative	None	0
	#20	Not significant	All stocks but those in Row #17	21
γ	#21	Positive	All stocks but those in Row #23	27
	#22	Significantly positive	BVT, CHE, CTP, ELH, HLH, NED, NPK, PAM, PPC, TBS, TNT	11
	#23	Negative	AFE, JCM, JNC, MAF, 0CE, REM, SBK, TRE, VNF, WLO	10
	#24	Significantly negative	None	0
	#25	Not significant	All stocks but those in Row #22	26
θ_1	#26	Positive	All stocks	37
	#27	Significantly positive	All stocks but that in Row #30	36
	#28	Negative	None	0
	#29	Significantly negative	None	0
	#30	Not significant	REM	1

Specifically, volatility was only prices in PORT, DUR, HAR and WAR, while only PORT and eleven stocks showed evidence of symmetric effects. The significant leverage effect parameters were positive, which was consistent with prior belief. Finally, the consequences of potential collinearity observed in the DGARCH model were also present.

As a further diagnostic checking of the DGARCH-M model, we conducted Ward tests for the joint significance of β and γ in the model. The null hypothesis was that $\beta = \gamma = 0$, and the resultant χ_2^2-distributed test statistics are presented in Table 7.

Table 7 – Ward tests for the DGARCH-M model

*This table shows the χ_2^2-distributed Ward test statistics (W) for the null hypothesis of $\beta = \gamma = 0$ in the DGARCH-M model. Figures in parentheses are the probabilities of accepting the null. NC indicates non-convergence in parameter estimation. * and ** imply that the null could be rejected at 1% and 5% significance levels, respectively.*

(a) Stock portfolios

Portfolio	*W*	*Security*	*W*
ALSI	0.309 (0.857)	PORT	7.286 (0.026)**

(b) Individual stocks

Security	*W*	*Security*	*W*
AFE	1.168 (0.558)	JCM	3.443 (0.179)
AFX	1.118 (0.572)	JNC	8.828 (0.012)**
AGL	NC	LGL	3.334 (0.189)
ALT	1.937 (0.380)	MAF	1.749 (0.417)

ANG	2.221 (0.329)	MLB	NC
ASR	NC	NED	10.139 (0.006)*
AVI	NC	NPK	1.844 (0.398)
BAW	NC	OCE	2.031 (0.362)
BVT	4.284 (0.117)	PAM	3.722 (0.156)
CHE	4.648 (0.098)	PIK	0.572 (0.751)
CRH	1.177 (0.555)	PPC	0.794 (0.672)
CTP	4.264 (0.119)	REM	0.774 (0.679)
DEL	NC	RLO	0.125 (0.940)
DUR	NC	SAB	0.824 (0.662)
ECO	3.255 (0.196)	SAP	3.100 (0.212)
ELH	5.929 (0.052)	SBK	0.548 (0.760)
FOS	4.744 (0.093)	TBS	5.415 (0.067)
GMF	1.005 (0.605)	TNT	3.215 (0.200)
HAR	4.861 (0.088)	TRE	10.222 (0.006)*
HLH	1.079 (0.583)	VNF	4.486 (0.106)
HVL	0.886 (0.642)	WAR	2.236 (0.327)
IMP	1.602 (0.449)	WLO	0.883 (0.643)

The Wald test results showed that, at a significance level of 5 percent, the null hypothesis could only be rejected for PORT, JNC, NED and TRE, in keeping with the observation that at least one of the two coefficients was significant for these series. This notwithstanding, and despite being the most log likelihood-preferred of the four models, there was no adequate motivation to choose the general DGARCH-M model as a description of univariate JSE equity returns. The stipulated evidence of collinearity and the fact that volatility was not commonly priced among the stocks rendered the model less useful.

4.5 Volatility Persistence

The estimated autoregressive parameters derived using (9), and their corresponding *t*-statistics[4] are shown in Table 8. In addition, the table shows the persistence measure given by the standard GARCH model, being the simple summation of the estimated ARCH and GARCH coefficients. In general, it was clearly evident that all the models exhibited very high volatility persistence. The estimated volatility measure implied by the standard GARCH model coefficients averaged 0.933 for the portfolios, and very closely approximated that of 0.935 for the individual stocks. The averages of the estimated autoregressive parameters for individual stocks ranged from a minimum of 0.869 in the DGARCH process to a maximum of 0.897 in the GARCH-M process. Therefore, by the autoregression gauge, the standard GARCH model exhibited a

[4] Note that the standard error of the autoregressive parameter is necessarily equal to one over the square root of the sample size.

persistence pattern in the region of the median of the persistence implied by all the models. A near-IGARCH process was generally suggested. Once again, the dynamics of individual stocks were quite well approximated by those of the aggregates.

Aside from the general conclusion that a near-IGARCH process seemed to describe the JSE, and notwithstanding few other cases in which the estimated autoregressive parameters were relatively low, it is noteworthy that the DGARCH model for AGL displayed 'outlier' behaviour, yielding a very low and statistically insignificant value. This was not particularly surprising, considering that the security showed the unique characteristic that even the GARCH term, let alone the ARCH term, yielded an insignificant parameter. The calculation of the mean autoregressive parameter estimate for individual stocks in the DGARCH formulation excluded this value.

The preceding analysis indicated that the standard GARCH model was the preferred description for the dynamics of JSE returns. Based on this empirical evidence, we proceeded to assess the model's ability to account for the non-linear structures established in Mangani (2005). The results of this investigation follow.

Table 8 – Volatility persistence in ARCH-type models

*In this table, ρ was estimated using (9). Figures in parentheses are t-statistics. NC denotes parameter non-convergence in model estimation. * indicates that the parameter was not significantly different from zero at all conventional levels.*

(a) Market aggregates

Portfolio	$\lambda_1 + \theta_1$	ρ							
		GARCH		*DGARCH*		*GARCH-M*		*DGARCH-M*	
ALSI	0.919	0.888	(27.327)	0.879	(27.050)	0.870	(26.773)	0.861	(26.496)
PORT	0.946	0.935	(36.393)	0.931	(36.237)	0.904	(35.186)	0.884	(34.408)
Mean	0.933	0.912		0.905		0.887		0.873	

(b) Individual stocks

Security	$\lambda_1 + \theta_1$	ρ							
		GARCH		*DGARCH*		*GARCH-M*		*DGARCH-M*	
AFE	0.939	0.903	(35.171)	0.903	(35.171)	0.859	(33.457)	0.857	(33.379)
AFX	0.931	0.911	(35.506)	0.918	(35.778)	0.934	(36.402)	0.949	(36.987)
AGL	1.009	0.996	(38.818)	0.006	(0.234)*	NC	-	NC	-
ALT	0.993	0.991	(38.585)	0.990	(38.546)	0.991	(38.585)	0.684	(26.632)
ANG	0.927	0.919	(35.817)	0.910	(35.467)	0.925	(36.051)	0.916	(35.701)
ASR	0.606	0.606	(23.618)	0.608	(23.696)	NC	-	NC	-
AVI	0.988	0.944	(36.731)	0.947	(36.848)	NC	-	0.949	(36.926)
BAW	0.954	0.831	(32.324)	0.855	(33.257)	NC	-	NC	-
BVT	0.873	0.838	(32.650)	0.813	(31.676)	0.829	(32.299)	0.805	(31.364)
CHE	0.881	0.902	(35.097)	0.952	(37.042)	0.932	(36.264)	0.968	(37.665)
CRH	0.942	0.857	(33.390)	0.945	(36.819)	0.945	(36.819)	0.943	(36.741)
CTP	0.985	0.964	(37.571)	0.952	(37.104)	0.972	(37.883)	0.959	(37.376)
DEL	1.012	0.924	(36.012)	0.936	(36.480)	NC	-	NC	-
DUR	0.553	0.485	(18.896)	0.438	(17.065)	0.505	(19.676)	NC	-

ECO	0.957	0.964	(37.398)	0.960	(37.243)	0.963	(37.359)	0.959	(37.204)
ELH	0.964	0.970	(37.718)	0.968	(37.640)	0.976	(37.951)	0.969	(37.679)
FOS	0.861	0.860	(33.485)	0.886	(34.497)	0.854	(33.251)	0.876	(34.108)
GMF	0.984	0.983	(38.312)	0.984	(38.351)	0.988	(38.507)	0.988	(38.507)
HAR	0.964	0.951	(37.040)	0.956	(37.235)	0.954	(37.157)	0.960	(37.391)
HLH	0.992	0.922	(35.934)	0.916	(35.701)	0.913	(35.584)	0.905	(35.272)
HVL	0.943	0.942	(36.653)	0.988	(38.443)	0.864	(33.618)	0.874	(34.007)
IMP	0.946	0.948	(36.923)	0.952	(37.079)	0.953	(37.118)	0.962	(37.469)
JCM	1.692	0.692	(26.872)	0.696	(27.028)	0.746	(28.969)	0.895	(34.756)
JNC	1.137	0.869	(33.227)	0.883	(33.762)	0.886	(33.877)	0.877	(33.533)
LGL	0.989	0.984	(38.351)	0.980	(38.195)	0.986	(38.429)	0.982	(38.273)
MAF	1.037	0.810	(31.496)	0.888	(34.529)	0.841	(32.702)	0.916	(35.618)
MLB	0.495	0.501	(19.526)	0.566	(22.059)	NC	-	NC	-
NED	0.942	0.948	(36.948)	0.940	(36.636)	0.952	(37.104)	0.950	(37.026)
NPK	0.979	0.986	(38.429)	0.977	(38.078)	0.963	(37.532)	0.976	(38.039)
OCE	0.977	0.960	(37.415)	0.958	(37.337)	0.968	(37.727)	0.968	(37.727)
PAM	0.819	0.792	(30.868)	0.825	(32.154)	0.798	(31.102)	0.827	(32.232)
PIK	0.942	0.939	(36.597)	0.911	(35.506)	0.975	(38.000)	0.969	(37.766)
PPC	0.972	0.969	(37.691)	0.973	(37.847)	0.969	(37.691)	0.973	(37.847)
REM	0.800	0.709	(27.606)	0.428	(16.665)	0.723	(28.151)	0.392	(15.263)
RLO	0.893	0.863	(33.579)	0.869	(33.813)	0.841	(32.723)	0.842	(32.762)
SAB	0.984	0.962	(37.493)	0.963	(37.532)	0.969	(37.766)	0.969	(37.766)
SAP	0.987	0.980	(38.195)	0.979	(38.156)	0.982	(38.273)	0.981	(38.234)
SBK	0.904	0.930	(36.043)	0.931	(36.082)	0.940	(36.430)	0.939	(36.392)
TBS	0.954	0.939	(36.476)	0.904	(35.117)	0.939	(36.476)	0.900	(34.961)
TNT	0.915	0.908	(35.389)	0.896	(34.921)	0.872	(33.986)	0.860	(33.518)
TRE	0.591	0.591	(23.034)	0.592	(23.073)	0.920	(35.856)	0.757	(29.504)
VNF	0.988	0.985	(38.377)	0.986	(38.416)	0.988	(38.494)	0.984	(38.338)
WAR	0.976	0.939	(36.585)	0.937	(36.507)	0.977	(38.065)	0.970	(37.793)
WLO	0.975	0.979	(38.143)	0.488	(19.013)	0.472	(18.390)	0.473	(18.429)
Mean	0.935	0.883		0.869[5]		0.897		0.891	

4.6 Linearity in the GARCH Model

Table 9 presents a summary of the BDS test statistics from the standardised residuals of the GARCH(1,1) model. Compared with the results for the linearly filtered return series reported in Mangani (2005), there was strong evidence that the GARCH model filtered most of the non-linearities in the return series. Specifically, no remaining non-linear structures could be observed in both portfolios and in seven individual stocks, and the magnitudes of the BDS statistics were drastically reduced in virtually all the cases. Moreover, of the forty-four stocks, at least one BDS statistic was insignificant in thirty-one. The results were quite similar to those obtained by Dockner *et al* (1997), who concluded that the DGARCH process accounted for most non-linearities on the Vienna Stock Exchange. The GARCH(1,1) model, therefore, showed promise in accounting for non-linearities on the JSE.

[5] Note that the calculation of this mean excluded the estimated ρ from the 'outlier' case, AGL. When this was included, the mean declined to 0.849

Table 9 – BDS tests for standardised GARCH(1,1) residuals: summary of findings for individual stocks

This tables summarises the BDS test results, presented in Appendix 4B, for the standardised GARCH(1,1) residuals. Results are for individual stocks. The stocks and numbers of stocks with significant BDS test statistics equal to the number in Column 1 are presented in Column 2 and Column 3, respectively. Column 4 and Column 5 give cumulative figures.

1 *# of Sig. Stat.*	*2* *Stocks*	*3* *# of Stocks*	*4* *# of Sig. Stat.*	*5* *# of Stocks*
0	ANG, ASR, BAW, NED, SBK, TBS, WAR	7	0	7
1	-	0	≤ 1	7
2	IMP, MAF	2	≤ 2	9
3	CHE, CRH, JNC	3	≤ 3	12
4	AFX, HLH	2	≤ 4	14
5	DUR, REM	2	≤ 5	16
6	AFE, HAR, PIK	3	≤ 6	19
7	-	0	≤ 7	19
8	BVT, PAM, TNT	3	≤ 8	22
9	DEL, ECO, JCM, OCE, PPC	5	≤ 9	27
10	GMF, RLO	2	≤ 10	29
11	CTP, FOS	2	≤ 11	31
12	AGL, ALT, AVI, ELH, HVL, LGL, MLB, NPK, SAB, SAP, TRE, VNF, WLO	13	≤ 12	44

The foregoing observation notwithstanding, it could still be noted from these results that some non-linear structures were existent in the standardised residuals from the GARCH model for the individual stocks. Therefore, the model with a time-varying conditional variance could account for most, but apparently not all, of the non-linearities. The remaining non-linear structures could indicate the presence of noise, low-order deterministic chaos, or additional linear dependencies not fully filtered through autoregression. Such linear dependencies could, for instance, be those associated with asset pricing anomalies, such as calendar, firm balance sheet and macroeconomic effects.

4.1 Summary and Conclusion

This paper investigated the usefulness of ARCH-type models in describing the return dynamics on the JSE. The investigation was premised on the validated evidence of volatility clustering prevalent on the market, as established in Mangani (2005). A specific-to-general modelling procedure was adopted in which the standard GARCH model was initially fitted to the return series, and eventually augmented in an attempt to capture the salient issues of interest. The GARCH(1,1) formulation was preferred relative to higher order GARCH specifications for all forty-six securities, of which two were stock portfolios and the rest were individual stocks. In order to investigate the presence of asymmetric effects of shocks on volatility, the dummy GARCH (DGARCH) model was preferred to the exponential GARCH (EGARCH) model on the basis of a statistical evaluation. Further, the GARCH-in-mean (GARCH-M) process was tested to investigate if volatility was priced on the market. Finally, to capture all the salient issues within one modelling framework, the more general dummy GARCH-in-mean (DGARCH-M) specification was invoked. The models were evaluated on the basis of statistical diagnostics. Several key conclusions can be drawn from the analysis, as follows.

Firstly, the inclusion of the asymmetric effects term was detrimental to the estimation of the standard GARCH model, to the extent that the term was highly collinear with the ARCH term. Thus, the parameters of the DGARCH model were imprecisely estimated, and there was no compelling evidence for leverage or even asymmetric effects of shocks on volatility.

Secondly, there was no evidence that volatility was a commonly priced factor on the market. Thus, although volatility was prevalent, JSE investors sought a premium for taking on other forms of perceived risk than volatility. Macroeconomic activities could provide effective surrogates for such priced factors. These two points imply that augmentations of the standard GARCH process did not improve the model's ability to explain the dynamics of the market. The standard model provided the best fit among the models, and showed potential as a framework for investigating further the stock return dynamics.

Finally, although the standard GARCH model performed relatively better than more complex formulations, it could only partially account for the evident non-linearities. Specifically, although the standardised residuals from the model showed that it was capable of accounting for a significant part of the non-linearities, it was evident that non-iid structures still remained in the series. This could imply that the remaining non-linear structures were deterministic (chaotic) rather than stochastic, or that additional linear dependencies existed in the data. Such dependencies could, for instance, be of the type associated with calendar effects, seasonalities or structural breaks, and could be a manifestation of the impact of broader macroeconomic activities.

Subsequent research could be motivated by the observation that volatility was not priced on the JSE, and that the standard GARCH model could not fully account for the non-linear structures. Such work could build on the current conclusion and investigate the relevance of macroeconomic activities in explaining the non-linear JSE stock return dynamics.

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Appendix 1 – Stocks in the study sample

This appendix shows the 44 stocks selected to constitute the final sample. UMC is the market capitalisation, before the application of the investibility weighting, while the WMC is the market capitalisation, after this application. UMC and WMC are in million rands.

#	JSE Code	Company Name	UMC (Rm)	WMC (Rm)	% of All Share Index
1	AFE	AECI Ltd	2346	2346	0.16
2	AFX	African Oxygen Ltd	4558	2279	0.15
3	AGL	Anglo American Plc	273677	273677	18.11
4	ALT	Allied Technologies Ltd	2383	1191	0.08
5	ANG	Anglogold Ltd	74176	37088	2.45
6	ASR	Assore Ltd	1820	0	0
7	AVI	Anglovaal Industries Ltd	4581	4581	0.3
8	BAW	Barloworld Ltd	14680	14680	0.97
9	BVT	The Bidvest Group Ltd	15415	15415	1.02
10	CHE	Chemical Services Ltd	1427	571	0.04
11	CRH	Coronation Holdings Ltd	1658	829	0.05
12	CTP	CTP Holdings Ltd	1930	579	0.04
13	DEL	Delta Electrical Industries Ltd	2409	2409	0.16
14	DUR	Durban Roodepoort Deep Ltd	9724	9724	0.64
15	ECO	Edgers Consolidated Stores Ltd	2039	2039	0.13
16	ELH	Ellerine Holdings Ltd	1255	1255	0.08
17	FOS	Foschini Ltd	2073	1555	0.1
18	GMF	Gencor Ltd	16802	0	
19	HAR	Harmony Gold Mining Co Ltd	28572	28572	1.89
20	HLH	Hunt Leuchars & Hepburn Holdings Ltd	1824	0	0
21	HVL	Highveld Steel Steel & Vanadium Corp. Ltd	1612	484	0.03
22	IMP	Impala Platinum Holdings Ltd	38649	28986	1.92
23	JCM	Johncom Communications Ltd	1354	0	0
24	JNC	Johnnic Holdings Ltd	7309	7309	0.48
25	LGL	Liberty Group Ltd	16526	8263	0.55
26	MAF	Mutual & Federal Insurance Co Ltd	4432	0	0
27	MLB	Malbak Ltd	2333	1166	0.08
28	NED	Nedcor Ltd	32370	16185	1.07
29	NPK	Nampak Ltd	7405	7405	0.49
30	OCE	Oceana Group Ltd	1536	614	0.04
31	PAM	Palabora Mining Company Ltd	1699	680	0.04
32	PIK	Pik n Pay Stores Ltd	6736	3368	0.22
33	PPC	Pretoria Portland Cement Co Ltd	3918	1567	0.1
34	REM	Remgro Ltd	34541	34541	2.29
35	RLO	Reunert Ltd	3999	3999	0.26
36	SAB	South African Breweries plc	71864	71864	4.76
37	SAP	Sappi Ltd	34068	34068	2.25
38	SBK	Standard Bank Group Ltd	47001	47001	3.11
39	TBS	Tiger Brands Ltd	12058	12058	0.8
40	TNT	The Tongaat-Hulett Group Ltd	4789	2394	0.16

41	TRE	Trencor Ltd	1383	0	0
42	VNF	VenFin Ltd	8708	8708	0.58
43	WAR	Western Areas Ltd	4315	3236.25	0.21
44	WLO	Wooltru Ltd	1792	1792	0.12
		Sample	**813746**	**694478**	**45.93**

(Source: Adapted from Profile Media, 2002).

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