CHANGES IN THE VOLATILITY LEVEL AND STRUCTURE OF SHARES POST SINGLE STOCK FUTURES TRADING

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Abstract

The introduction of single stock futures to a market presents the opportunity to assess an individual company's response to futures trading directly, in contrast to the market-wide impact obtained from index futures studies. The listed shares of thirty-eight South African companies were evaluated in terms of a possible volatility effect due to the initial trading of their respective single stock futures contacts. A GARCH(1,1) model established a volatility structure (pattern of behaviour) per company. Results, in general, showed a reduction in the level and changes in the structure of spot market volatility post single stock futures.

Keywords: Single stock futures, equity shares, GARCH model, volatility level, volatility structure, spot market, futures market

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1 Introduction

Single stock futures, also known as individual equity futures, are exchange-traded future commitments to buy or sell the shares of a particular listed company at a predetermined price. Being derived from and therefore reliant on the price of an ordinary share and accepting that a futures price is determined in large by its underlying spot price it is conceivable that a reciprocal relationship exists between the underlying equity share and its derivative, raising the question as to what extent does the derivative impact upon the underlying.

Several studies reported on the change (if any) in the level of spot volatility after single stock futures trading commenced. Peat and McCorry (1997) performed a regression analysis (incorporating a volume effect) and a t-test for change in mean on ten individual equity shares listed in Australia and concluded that an increase in the underlying volatility resulted from SSF trading. This reported effect on the Australian market, however, could not be confirmed by Lee and Tong (1998) or Dennis and Sim (1999). An equal means and equal variances t-test and rank sum tests with a control group sample, and an asymmetric exponential ARCH model study respectively, provided no evidence of returns becoming more volatile after futures trading.

The following studies employed GARCH methodology to also report on possible changes in the structure of volatility post SSF trading, in addition to the level of volatility. McKenzie, Brailsford and Faff (2001) evidenced a decline in unconditional volatility and some changes in the dynamics by which the conditional volatility evolves – that is, a slower dissemination and shorter impact of news (decline in ARCH and GARCH terms) by the underlying ten Australian-listed shares. Similar results came from research by Hung, Lee and So (2003). The nine individual results (universal stock futures i.e., UK listed single stock futures on foreign equity markets) favoured a slower dissemination and shortened impact of information, leading to a lower persistence of volatility in general. The variances (unconditional volatility) of the underlying share returns showed no significant differences between the pre- and post-introduction groups.

Eighty individual equity shares featured in a study by Chau, Holmes and Paudyal (2005), also regarding the impact of universal stock futures. Any changes in the GJR-GARCH model parameters (i.e., impact of news on volatility; persistence of innovations; asymmetric response to good and bad news) concluded not to be futures related after examining the control sample. Unconditional volatility also behaved in a similar manner for both SSF and control shares. Therefore, no volatility effect as a result of SSF trading in contrast to Mazouz and Bowe (2006), who studied the response of twenty-one UK-listed shares. They attributed a decrease in unconditional volatility post futures to contemporaneous changes in market- and industry-wide conditions and not to the listing event, per se. Their evidence, however, also pointed to a more efficient (faster) incorporation of current news into the underlying share price owing to futures trading.

The limited number of studies carried out to date concerning the effects of single sock futures trading on the underlying cash market, and the many studies featuring share index futures trading (see for example

Darrat & Rahman 1995; Butterworth 2000; Bologna & Cavallo 2002; Kumar & Mukhopadhyay 2004; Bae, Kwon & Park 2004; Drimbetas, Sariannidis & Porfiris 2007), and equity (individual or index) options/warrants (see for example Elfakhani & Chauhury 1995; Chatrath, Ramchander & Song 1995; Faff & Hillier 2005; Mazouz 2004; Aitken & Segara 2005; Clarke, Gannon & Vinning 2007), presented diverse results and highlighted the continued uncertainty surrounding the impact of futures trading on the spot market.

Globally single stock futures represent a new type of derivative, and the impact of their introduction on the underlying domestic equity markets has not been evaluated extensively to any degree (confined to the UK and Australian markets). Research on the effect of futures trading on the South African market (see Oehley 1995; Parsons 1998; Smit & Nienaber 1997; Vanden Baviere & De Villiers 1997; Swart 1998; Kruger 2000) is by no means exhaustive, and the introduction of single stock futures to this market in 1999 provided an unique opportunity for a more direct assessment of the possible impact on the behaviour of the underlying shares.

The purpose of this research was to determine the impact of SSF-trading on the underlying in terms of a possible volatility effect, and to record a distinct response to news for each of the companies included in the study.

2 Research methodology

This study employed the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) methodology as a measure to detect changes in the conditional variance (structure of volatility) and unconditional variance of the error terms (level of volatility). The impact of a security-specific event on the level or degree of the security's price changes and the duration thereof is modelled as the conditional variance of the security. An increase or decrease in the post-event unconditional variance of the security is detected by the relative changes in parameter values as specified by the GARCH model.

2.1 Autoregressive conditional heteroskedasticity

An ordinary least squares regression model is subject to the condition that the variance of the error term is constant. The expected value of all error terms or residuals, when squared, should be the same at any given point. In other words, the variances of the error terms must remain constant with time. This assumption is referred to as homoskedasticity. The violation of this constant variance assumption is the basis for ARCH/GARCH models. Therefore, when a time series is heteroskedastic, it exhibits time-varying variance (i.e., volatility) and is said to have ARCH effects.

As stated, heteroskedasticity is associated with time-varying volatility. Also, "conditional" implies a dependence on the observations of the immediate past, and "autoregressive" describes a feedback mechanism that incorporates past observations into the present (Mathworks 2006:1.3). Autoregressive conditional heteroskedasticity (ARCH), therefore, describes the condition where the variance of the residuals in one period within a time series is dependent on, or is a function of, the variance of the residuals in another preceding period. If this condition exists, the standard errors of the regression coefficients in autoregressive (AR) models and the hypothesis tests of these coefficients will be invalid. But, as stated by Engle (2001:157), "Instead of considering this as a problem to be corrected, ARCH and GARCH models treat heteroskedasticity as a variance to be modelled." GARCH models are mean reverting and conditionally heteroskedastic, with a constant unconditional variance. Therefore, the least squares deficiencies are corrected and the required conditions satisfied.

ARCH models are specifically designed to model and forecast conditional variances. The variance of the dependent variable is modelled as a function of past values of the dependent variable and independent variables. ARCH models were introduced by Engle (1982) and generalised as GARCH (Generalised ARCH) by Bollershev (1986). The standard GARCH(p,q) suggests that the conditional variance of returns is a linear function of lagged conditional variance terms and past squared residual terms (Butterworth 2000:440).

GARCH (p,q) is the standard notation in which the first number (p) refers to the number of autoregressive lags (ARCH terms) and the second number (q) refers to the number of moving average lags (GARCH terms). GARCH(1,1) therefore refers to the presence of a first order ARCH term and a first order GARCH term (Engle 2001:160).

INSERT FIGURE 1 ABOUT HERE

The GARCH process, exhibited in figure 1, is characterised by volatility clustering – that is, tranquil periods interspersed with periods of high volatility. Variance, rather than being constant, is an autoregressive (AR) process where the current period's volatility is conditional on past (lagged) volatility (Miles 2008:75).

2.2 Specification of the GARCH(1,1) model

In developing a GARCH model, two distinct specifications have to be provided – one for the conditional mean (1) and one for the conditional variance (2). The conditional variance equation is a function of three terms, namely the

- mean or constant: ω (long-term average)

- information about the volatility of the previous period, measured as the lag of the squared residual from the mean equation: ε_{t-1}^2 (ARCH term)
- forecasted variance from the last period: h_{t-1} (GARCH term)

The conditional mean equation (1) contains an autoregressive component that explains the current asset price. The GARCH model is captured by (2) where the variance of the error terms has been modified from being assumed to be constant to being time varying. The GARCH(1,1) parameterisation for the conditional variance implies that current volatility depends on past squared error terms and an autoregressive component of the conditional variance. The parameters of the GARCH(1,1) model are estimated using maximum likelihood under the assumption of conditional normality (Brooks 2002:456).

Brooks (2002:455-458) describes the maximum likelihood technique as essentially finding the most likely values of the parameters given the actual data. A statistical software programme employing iterative techniques generates the parameter values and associated standard errors that maximise the LLF. Therefore, given a set of initial "guesses" for the parameter estimates, these parameter values are updated at each iteration until an optimum is reached (i.e., convergence). Convergence is achieved and the programme will stop searching when the biggest percentage change in any of the parameter estimates for the most recent iteration is smaller than 0,01% (default setting). This iterative procedure using a modification of the Berndt, Hall, Hall and Hausman (BHHH) algorithm for optimisation, namely the Marquardt algorithm, incorporates a correction, pushing the parameter estimates more quickly to their optimal values. An assumption about the conditional distribution of the error term is required and the normal (Gaussian) distribution, Student's t-distribution, and the Generalised Error Distribution (GED) are assumptions commonly employed when working with ARCH models. The Heteroskedasticity Consistent Covariance option is available when selecting the conditional normal as the error distribution, thereby calculating the quasi-maximum likelihood (QML) covariances and standard errors using the robust-to-non-normality method of Bollershev-Wooldridge (EViews 2007b:187,192).

AR(1)-GARCH (1,1) model specification

Conditional mean equation

$$y_t = a + by_{t-1} + \varepsilon_t \qquad ; \ \varepsilon_t \sim N(0, h_t) \tag{1}$$

Conditional variance equation

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \quad ; \omega > 0, \alpha > 0, \beta \geq 0 \tag{2}$$

Unconditional (constant) variance of the error term

$$\operatorname{var}(\varepsilon_t) = \frac{\omega}{1-(\alpha+\beta)} \tag{3}$$

Specification of the log-likelihood function (LLF)

$$L = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log(h_t) - \frac{1}{2}\sum_{t=1}^{T}\frac{(y_t - a - by_{t-1})^2}{h_t} \tag{4}$$

Where:

y_t = Dependent variable (return on an asset)

a = Constant

by_{t-1} = Autoregressive coefficient and explanatory (lagged) variable

ε_t = Error term

And:

h_t = Conditional variance in period t

ω = Constant (long-term average)

$\alpha\varepsilon_{t-1}^2$ = News coefficient and ARCH(1) term

βh_{t-1} = Persistence coefficient (old news) and GARCH(1) term

Source: Adapted from Brooks (2002:455-457)

If convergence is not achieved or implausible (i.e., parameter values are negative or too large) when parameter estimates are obtained with the default estimation settings, the estimation could be redone with different starting values (programme assigns its own starting values using OLS regression for the mean equation), and/or by selecting a different error distribution to the Normal (Gaussian), increasing the maximum number of iterations or adjusting the convergence criterion. The parameters should be positive and should add up to a number less than one (required for a mean reverting variance process). A variety of views and procedures for inference and diagnostic checking are available to detect model failures (Engle 2001:161; EViews 2007b:192,195).

A GARCH model is parsimonious (i.e., the coefficients of the model are easily interpreted) and gives significant results, since it allows the conditional variance of an asset price to be dependent upon previous own lags (Floros 2007:363). The advantage of a GARCH model, according to Joshi and Pandya (2008:9) and Samanta and Samanta (2007:57), is the ability to capture the tendency in financial data for volatility clustering, thereby enabling an explicit connection between information and volatility. Any change in the rate at which information arrives in the market will change the volatility in the market. According to Engle (1993:72), volatility clustering or pooling is one of the oldest noted characteristics of financial data. Periods of high/low volatility are likely to be followed by subsequent periods of high/low volatility, attesting to the predictability of volatility. The implication of such volatility clustering is that current volatility shocks will influence future expectations of volatility (Engle & Patton 2001:239). It is therefore beneficial to determine statistically whether recent information is more important than old information, and how fast information decays. Samanta and Samanta (2007:61) state that the GARCH equation has two effects: the effect of recent news to the market (ARCH effect) and the effect of the old news in the market (GARCH effect). Variation in the size of these two effects determines the current or lingering influence of news on the market; with the sum of these effects indicating the degree of persistence in volatility.

In summary: A significant ARCH or GARCH term in the variance equation implies that the sample follows a persistent clustered volatility process – that is, once there is a shock or jolt to the share price, the impact is more likely to persist for several subsequent periods. An insignificant ARCH or GARCH would indicate that the impact only would last for one period. A large ARCH or GARCH term in the variance equation similarly would indicate that the impact of a shock to the share price is likely to persist for several subsequent periods. A small ARCH or GARCH term implies a short-lived impact on the underlying. Correspondingly, an increase/decrease in the ARCH(1) coefficient suggests a faster/slower dissemination of news and apparent impact on the share price, while an increase in the GARCH(1) coefficient implies a prolonged effect of past news on the underlying. A summed ARCH (new news) and GARCH (old news) value, the autoregressive root, reveals the propensity or inclination of a particular share to exhibit the impact and after-effect of a shock (i.e., unexpected news) on its price. The size of the autoregressive root (AR root) signifies the possible extent of any shock effect, namely the "persistence to shocks". An AR root of less than one (unity) indicates a stationary and predictable volatility (Steeves 2002:43; Butterworth 2000:440; Bologna & Cavallo 2002:189).

Morimune (2007:4-5) states that for GARCH(1,1) the conditions of $\omega > 0$, $\alpha > 0$ and $\beta \geq 0$ are sufficient to ensure a strictly positive conditional variance, $h_t > 0$. The ARCH (α) effect captures the short-run persistence of shocks and the GARCH (β) effect indicates the contribution of shocks to the long-run persistence ($\alpha+\beta$) of volatility. The necessary and sufficient condition for the existence of variance stationarity (i.e., a defined mean-reverting level) is ($\alpha+\beta$) < 1. This is reiterated by Floros (2007:363) who states that all parameters must be positive, with the sum of α and β expected to be less than but close to unity, with $\beta > \alpha$. The value of ω (constant) is also expected to be small. Samouilhan (2007:105) explains that with the combined value (i.e., the autoregressive root) closer to unity, persistence declines slowly and there is much volatility clustering. In the extreme cases where ($\alpha+\beta$) = 1, the shock-effect never dissipates, and with ($\alpha+\beta$) = 0 the shock dies out immediately (i.e., no ARCH effects).

A pre-event subsample and a post-event subsample are tested separately for ARCH(1) and GARCH(1) effects. The significance, size and change in coefficients from equation (2) are evaluated, and the unconditional variance (3) calculated so long as ($\alpha+\beta$) < 1. For ($\alpha+\beta$) ≥ 1, the unconditional variance is not defined and labelled as "non-stationary in variance". A change in the ω coefficient post-event relative to the change in the autoregressive root ($\alpha+\beta$) confirms an increase or decrease in the unconditional (long-term average) variance of a security (Butterworth 2000:441).

Alternatively, any change in the unconditional variance of an asset price after the event can be detected by augmenting (2) to include a dummy variable (5). The dummy variable is equal to 0 for all pre-event periods and to 1 afterwards.

$$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} + \delta D_F \qquad (5)$$

$$\operatorname{var}(\varepsilon_t) = \frac{\omega + \delta}{1-(\alpha+\beta)} \qquad (6)$$

Where:

δ	=	Coefficient
D_F	=	Dummy variable

The unconditional variance for the period after the event is then calculated as in (6), as opposed to (3). A significant positive (negative) coefficient points to an increase (decrease) in the volatility as a result of futures trading (Samanta & Samanta 2007:61).

2.3 Diagnostic tests

The Ljung-Box Q-statistic test with a specified number of lagged autocorrelations is utilised to test whether the ARCH/GARCH model adequately captured all of the persistence in the variance of returns. This requires an inspection of the correlogram (autocorrelations and partial autocorrelations) of the squared standardised residuals (Engle & Patton 2001:242; EViews 2007a:326). If the variance equation is specified correctly all Q-statistics should not be significant (i.e., squared standardised residuals serially uncorrelated). The specification of the mean equation can similarly be checked and tested for remaining serial correlation by looking at the correlogram of the standardised residuals with all Q-statistics expected not to be significant (EViews 2007b:195).

The ARCH LM test carries out Lagrange multiplier tests to test whether the standardised residuals exhibit additional ARCH. A correctly specified variance equation should exhibit no ARCH in the standardised residuals. Two test statistics, namely the F-statistic and the Obs*R-squared statistic, are reported from this test regression (EViews 2007b:158,196).

The Jarque-Bera (JB) statistic tests the null of whether the standardised residuals are normally distributed. If the standardised residuals are normally distributed, the Jarque-Bera statistic should not be significant. The difference between the skewness (i.e., extent not symmetric about mean value) and kurtosis (i.e., "peakedness" and "fat tails" of distribution – related to frequency and size of deviations) of the series and those from the normal distribution is measured. A small reported probability (p-value) leads to the rejection of the null hypothesis of a normal distribution. The Jarque-Bera statistic follows the chi-squared distribution with 2 degrees of freedom (EViews 2007a:308; EViews 2007b:195). Even if the conditional normality assumption does not hold, the parameter estimates will still be consistent if the mean and variance equations are specified correctly. However, the usual standard errors estimates will be inappropriate requiring the Heteroskedasticity Consistent Covariance option (available in the statistical software programme) to be selected, calculating the Bollershev-Wooldridge robust standard errors (Brooks 2002:461). The Student's t-distribution and GED (fat tail distributions) capture the non-normal aspects of the data and provide an alternative solution for the non-normality of the residuals (Samouilhan & Shannon 2008:23).

3 Statistical analysis

The South African market saw three-hundred and fifty-seven (357) first-time introductions (available for trade) of physically-settled SSF contracts from 1999 to 2007. Thirty-eight (38) companies matched the following criteria for inclusion in the study (refer to Appendix A).

- No direct or indirect prior introductions of SSF contracts.
- Trading activity – available for trade and the actual trading of contracts occurring within a two week period.
- 250 days of spot trading before and after the event.

The inherent volatility clustering present in equity returns can be seen in figure 2 (DDT daily-returns) which exhibits significant levels of volatility persistence; large movements (magnitude of returns) are clustered with large movements, and small movements clustered with small movements.

INSERT FIGURE 2 ABOUT HERE

Each of the thirty-eight companies exhibited a similar individually defined and unique response to news (De Beer 2008:85). Illustrated by means of the DDT case. Results for Dimension Data Holdings (11 – DDT) shows statistically significant small and decreasing ARCH values with large and increasing GARCH values, pre to post SSF-trading (see table 1). The size of the AR root is indicative of a high persistence to shocks (i.e., volatility clustering) and therefore predictable volatility (function of past volatility). The direction of change after initial SSF-trading reveals a slower dissemination but longer lasting impact of information. This would suggest that the trading of SSF contract has attracted additional, relatively uninformed traders to both the futures and spot markets, leading in turn to a smaller immediate response to news and to news having a more persistent impact on the spot market. The total period coefficients (see table 2) confirms that Dimension Data returns exhibited a pattern of persistent volatility clustering (significant ARCH and GARCH terms), and indicates a decrease (non-significant dummy variable coefficient) in volatility post SSF-trading.

The Ljung-Box Q-statistics provided evidence that the GARCH model adequately captured all of the persistence in the variance of returns, with no statistically significant Q-stats. The variance equation proved to be specified correctly with no remaining ARCH detected. Similarly, the mean equation was tested for any remaining serial correlation with the Q-stats all reported to be non-significant as expected (De Beer 2008:83).

The ARCH LM test carried out on the variance equation exhibited no ARCH in the standardised residuals with both the F-statistic and the Obs*R-squared statistic, reported as non-significant in contrast to the regression results before applying the GARCH concepts showing statistical significance and heteroskedasticity (De Beer 2008:83).

The Jarque-Bera (JB) statistic, testing the null of whether the standardised residuals are normally distributed, is significant and consequently the conditional normality assumption does not hold. This required the Heteroskedasticity Consistent Covariance option to be selected with the Normal (Gaussian) error distribution in order to calculate the Bollershev-Wooldridge robust standard errors. The parameter estimates, however, are still consistent when the mean and variance equations are correctly specified (De Beer 2008:83) .

These diagnostics tests are important when GARCH-model values are used to predict future volatility. Attempting to detect a change in the level (unconditional volatility) and structure (conditional volatility) of volatility from one period to another (e.g., pre- to post-futures) simply requires a comparison of the relative values and direction of change. For the purposes of this study, the conditions of $\omega > 0$, $\alpha > 0$, $\beta \geq 0$ and $(\alpha+\beta) < 1$ were necessary and sufficient to ensure a positive conditional variance and the existence of variance stationarity (i.e., a defined mean-reverting level). All parameters must therefore be positive, with the sum of α and β expected to be less than but close to unity, with $\beta > \alpha$. Subject to these conditions, the ARCH/GARCH results for the thirty-eight companies are presented and interpreted in tables 1 and 2. These results are summarised in table 3 and presented graphically in figure 3 in an attempt to determine the general impact of initial SSF-trading on the level and structure of spot market volatility.

Table 1 shows the changes in pre to post SSF-period ARCH and GARCH effects for all thirty-eight companies. The preferred outcome of futures trading is a more efficient market, namely a faster dissemination of news by the underlying share price, a shorter-lived after-effect, and subsequently a less persistent shock-effect on the share price. This translates into a larger ARCH-term, a smaller GARCH-term and smaller AR root (ARCH plus GARCH). Eleven companies experienced this desired result (full benefit) attributed to futures trading (refer to table 3). The statistical output of eight companies confirmed that futures trading had the exact opposite consequence for the behaviour of their share prices. A decreased ARCH and increased GARCH expose a more persistent shock-effect due to the longer lasting influence of old news which, initially, was incorporated into the share price at a slower pace, since the start of SSF-trading.

INSERT TABLE 1 ABOUT HERE

Table 2 shows the per-company results for the total period with the dummy variable coefficient (δ) revealing any possible change in the level of volatility in each instance. The ARCH and GARCH coefficients reveal each company's tendency to experience volatility clustering.

INSERT TABLE 2 ABOUT HERE

A significant ARCH or GARCH term implies that the share returns exhibited a pattern of persistent volatility clustering, meaning that once there is a shock or jolt to the share price, the impact is more likely to persist for several subsequent periods. An insignificant ARCH or GARCH indicate that the impact only lasted for one period. As can be expected from financial data, all companies with the exception of Lonmin PLC (26 – LON) exhibited some tendency for volatility clustering (significant ARCH and/or GARCH term).

4 Summary of results

Figure 3 graphically depicts and table 3 summarises the individual company results post-futures with the majority (17 from 20) showing a statistically significant increase in the dissemination rate of news. Thirteen statistically significant instances of a reduced contribution to persistence by past news were also recorded among the twenty-one (majority) companies exhibiting this tendency. Overall, more companies (20) showed a shortened period of excessive price movements following the incorporation of news, compared to those (18) showing an increased persistence to shocks (extended period of volatility). However, more statistically significant increases (16 from 17) in the long-term impact of old news were recorded.

INSERT FIGURE 3 ABOUT HERE

The dummy variable included in the GARCH model revealed that the majority of companies (32) experienced a decrease in the level of spot volatility, with only ten showing a statistically significant decrease. It is therefore reasonable to conclude that the introduction of futures trading generally subdues movements in share prices (i.e., volatility).

INSERT TABLE 3 ABOUT HERE

5 Conclusion

Regarding the structure or behaviour of volatility, the majority (53% of which 85% were statistically significant) of companies showed an increase in the rate at which news is disseminated and incorporated into their share prices. However, although more companies (55%) displayed a smaller contribution of old news to persistence, more statistically significant increases (42% to 34% significant decreases) in the long-term impact of old news were recorded. The combined outcome (incorporation plus longevity) pointed towards a shortened period of excessive price-movements (persistence of volatility or shocks) following the incorporation of news for a small majority (53%) of companies. The dummy variable included in the GARCH model confirmed that the majority (84% of which 31% were statistically significant) of companies experienced a decrease in the level of spot volatility.

Overall, results indicated that SSF trading allowed the shock effect to dissipate more quickly, largely facilitated by the faster dissemination of news and also, to a lesser extent, by the constrained influence of old news on share prices, thereby providing for a more efficient market. This study provided evidence that single stock futures trading activity does impact upon the volatility level and volatility structure of the underlying equity shares. In addition, each of the thirty-eight South African companies recorded a distinct response to news.

Note

This article is based on a study done on the impact of single stock futures on the South African equity market that also reported on any changes in the price and trading volume of the underlying, post initial single stock futures trading.

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Appendices

Figure 1. GARCH process

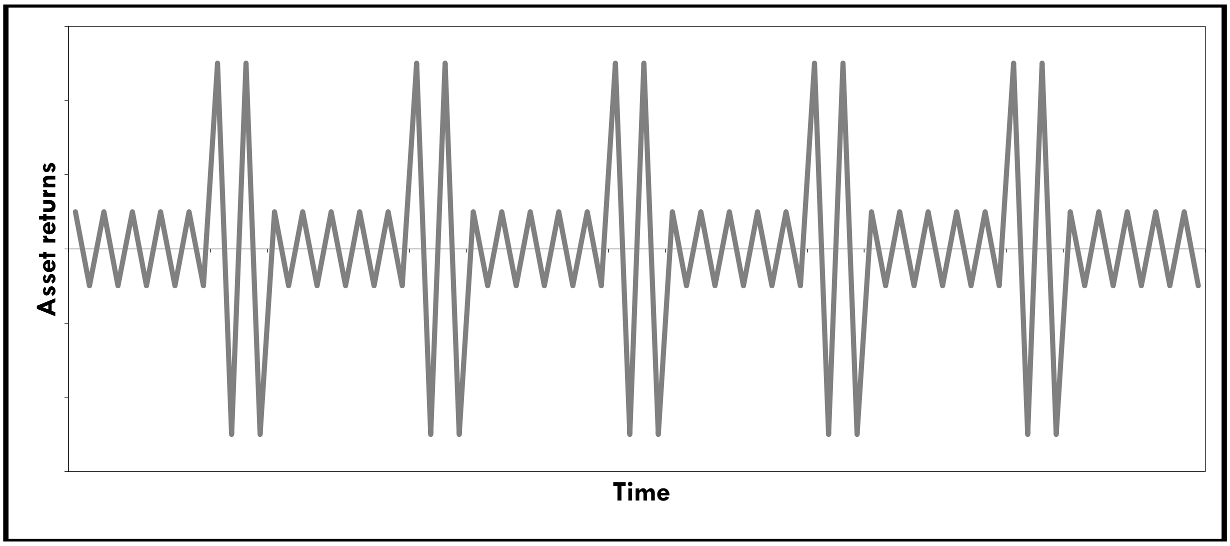
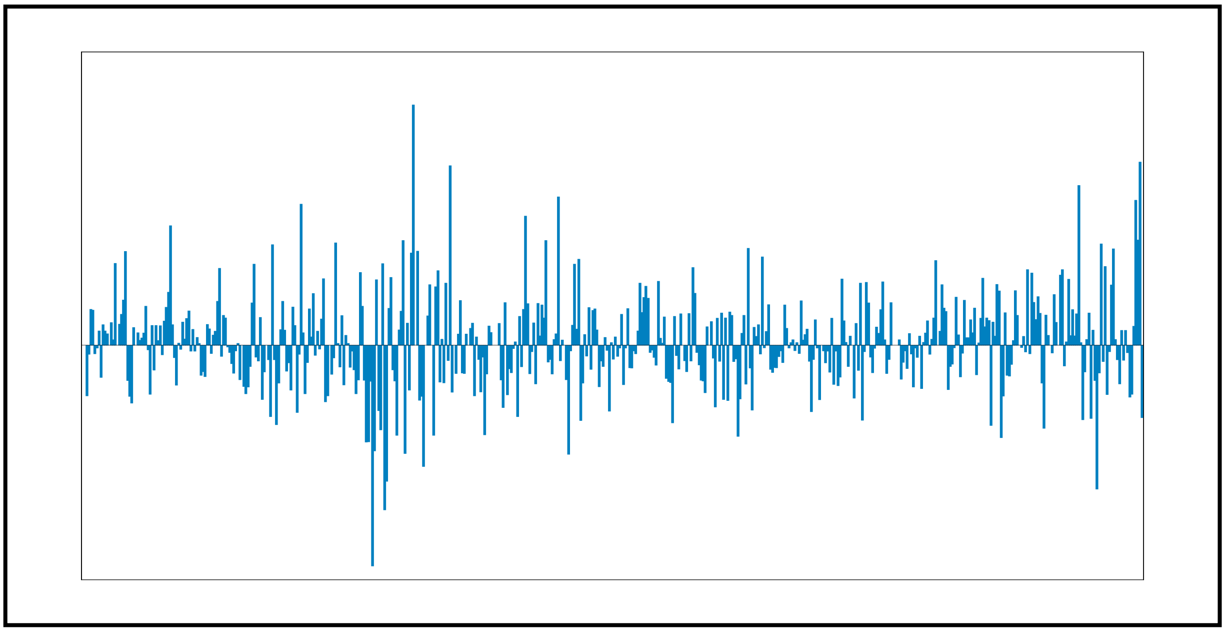


Figure 2. Daily returns – Dimension Data Holdings (11 – DDT)



Source: McGregor-BFA (EViews6 generated)

Table 1. Changes in pre to post SSF-period ARCH and GARCH effects

The table shows the results from an ARCH/GARCH variance regression for the pre-SSF period and post-SSF period. The mean equation [$y_t = a + by_{t-1} + \varepsilon_t$] generated the residuals for the variance equation, estimated by regressing the lognormal share-returns on the one-period lagged returns of each share. The variance equation [$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}$] produced the ARCH and GARCH terms for the pre- and post-period. The autoregressive root (α+β) governs the persistence of volatility shocks.

Company	Pre-SSF			Post-SSF		
	ARCH (α)	GARCH (β)	α+β	ARCH (α)	GARCH (β)	α+β
1 AFE	0.06097 (0.2759)	0.75175 (0.0006)**	0.81272	0.07062 (0.3618)	0.64107 (0.0622)*	0.71169
2 AFL	0.05353	0.93093	0.98446	0.11798	0.80965	0.92763

The table shows the results from an ARCH/GARCH variance regression for the pre-SSF period and post-SSF period. The mean equation [$y_t = a + by_{t-1} + \varepsilon_t$] generated the residuals for the variance equation, estimated by regressing the lognormal share-returns on the one-period lagged returns of each share. The variance equation [$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}$] produced the ARCH and GARCH terms for the pre- and post-period. The autoregressive root (α+β) governs the persistence of volatility shocks.

Company	Pre-SSF			Post-SSF		
	ARCH (α)	GARCH (β)	α+β	ARCH (α)	GARCH (β)	α+β
	(0.1193)	(0.0000)***		(0.0604)*	(0.0000)***	
3 ALT	0.06371 (0.2430)	0.73571 (0.0296)**	0.79942	0.07393 (0.2155)	0.78136 (0.0002)***	0.85529
4 AMA	0.01072 (0.8236)	0.75986 (0.5486)	0.77057	0.09949 (0.0480)**	0.72699 (0.0000)***	0.82648
5 APK	0.03597 (0.0110)**	0.89954 (0.0000)***	0.93551	0.23549 (0.1246)	0.69278 (0.0000)***	0.92828
6 ART	0.16670 (0.3322)	0.46388 (0.2791)	0.63057	0.21309 (0.0786)*	0.51674 (0.0498)**	0.72983
7 BRC	0.05319 (0.3630)	0.53549 (0.1913)	0.58568	0.13744 (0.0777)*	0.57130 (0.0033)***	0.70874
8 CDZ	0.03598 (0.6444)	0.80366 (0.0909)*	0.83964	0.25120 (0.0553)*	0.33982 (0.2204)	0.59102
9 CPT	0.07150 (0.3829)	0.67194 (0.0566)*	0.74344	0.24250 (0.1317)	0.34198 (0.2679)	0.58448
10 CSB	0.05686 (0.4259)	0.47605 (0.4552)	0.53291	0.21998 (0.1586)	0.51201 (0.0374)**	0.73199
11 DDT	0.08021 (0.0529)*	0.88633 (0.0000)***	0.96654	0.04065 (0.0714)*	0.95154 (0.0000)***	0.99219
12 DGC	0.33948 (0.0081)***	0.49727 (0.0000)***	0.83674	0.06225 (0.4706)	0.47650 (0.5287)	0.53875
13 DUR	0.24791 (0.1149)	0.25832 (0.5180)	0.50623	0.19437 (0.0491)**	0.57391 (0.0068)***	0.76828
14 EOH	0.07496 (0.3164)	0.53807 (0.1941)	0.61304	0.25101 (0.0072)***	0.52451 (0.0043)***	0.77551
15 ERM	0.01681 (0.0230)**	0.96919 (0.0000)***	0.98600	0.09958 (0.1153)	0.66690 (0.0006)***	0.76649
16 GDF	0.09428 (0.0598)*	0.43802 (0.1175)	0.53230	0.09359 (0.1494)	0.58299 (0.0286)**	0.67658
17 GIJ	0.16391 (0.0225)**	0.81715 (0.0000)***	0.98106	0.14312 (0.1978)	0.82718 (0.0000)***	0.97031
18 GND	0.13086 (0.0065)***	0.81881 (0.0000)***	0.94967	0.16295 (0.0387)**	0.75062 (0.0000)***	0.91357
19 HDC	0.14115 (0.0712)*	0.58340 (0.0157)**	0.68065	0.07317 (0.4381)	0.55484 (0.2801)	0.62801
20 JCD	0.22800 (0.0035)***	0.67368 (0.0000)***	0.90167	0.28755 (0.0715)*	0.41480 (0.0597)*	0.70235
21 JSC	0.19066 (0.0184)**	0.59842 (0.0035)***	0.78908	0.12312 (0.0549)*	0.77932 (0.0000)***	0.90244
22 KAP	0.34319 (0.0004)***	0.44405 (0.0000)***	0.78725	0.07388 (0.5270)	0.58118 (0.4438)	0.65506
23 KGM	0.04095 (0.1400)	0.49165 (0.3479)	0.53259	0.11122 (0.1091)	0.56515 (0.0187)**	0.67637
24 KWV	0.03805 (0.1320)	0.68682 (0.0002)***	0.72487	0.01120 (0.4981)	0.80171 (0.0292)**	0.81292
25 LBH	0.06947 (0.0930)*	0.67953 (0.0088)***	0.74899	0.04056 (0.5875)	0.39813 (0.6737)	0.43869
26 LON	0.12871 (0.0313)**	0.55099 (0.0012)***	0.67970	0.14757 (0.1688)	0.41585 (0.2433)	0.56342
27 MCE	0.35292 (0.0005)***	0.52597 (0.0000)***	0.87889	0.09774 (0.0725)*	0.82592 (0.0000)***	0.92366
28 OMN	0.09085 (0.0891)*	0.66018 (0.0001)***	0.75102	0.69116 (0.0001)***	0.24646 (0.0193)**	0.93762

The table shows the results from an ARCH/GARCH variance regression for the pre-SSF period and post-SSF period. The mean equation [$y_t = a + by_{t-1} + \varepsilon_t$] generated the residuals for the variance equation, estimated by regressing the lognormal share-returns on the one-period lagged returns of each share. The variance equation [$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1}$] produced the ARCH and GARCH terms for the pre- and post-period. The autoregressive root (α+β) governs the persistence of volatility shocks.

Company	Pre-SSF			Post-SSF		
	ARCH (α)	GARCH (β)	α+β	ARCH (α)	GARCH (β)	α+β
29 PCN	0.17082 (0.1225)	0.54690 (0.0479)**	0.71772	0.06366 (0.1033)	0.86583 (0.0000)***	0.92949
30 PIM	0.10258 (0.0498)**	0.82079 (0.0000)***	0.92336	0.11672 (0.0968)*	0.78482 (0.0000)***	0.90153
31 PWK	0.07252 (0.1146)	0.78585 (0.0000)***	0.85837	0.00006 (0.2120)	0.56927 (0.0463)**	0.67889
32 SGG	0.42088 (0.0908)*	0.53589 (0.0019)***	0.95677	0.07313 (0.7349)	0.20923 (0.9327)	0.28236
33 SHP	0.04565 (0.2829)	0.89708 (0.0000)***	0.94273	0.29240 (0.0813)*	0.47783 (0.0194)**	0.77023
34 SIM	0.08857 (0.1599)	0.78156 (0.0001)***	0.87013	0.07476 (0.0099)***	0.91705 (0.0000)***	0.99181
35 SLM	0.31250 (0.1186)	0.43447 (0.1907)	0.74697	0.15699 (0.2106)	0.58371 (0.1071)	0.74069
36 SPG	0.32256 (0.0578)*	0.56937 (0.0005)***	0.89193	0.20658 (0.2148)	0.36224 (0.2204)	0.56882
37 UCS	0.20572 (0.0139)**	0.60643 (0.0000)***	0.81215	0.07893 (0.2979)	0.32011 (0.6875)	0.39904
38 WNH	0.10540 (0.3780)	0.55214 (0.2030)	0.65754	0.29237 (0.0159)**	0.47090 (0.0007)***	0.76327

Notes:
- Default: Normal (Gaussian) error distribution with OLS starting values
- Alternative distributions: Student's t (optional fixed degrees of freedom) and GED (optional fixed parameter)
- Starting coefficients generated with Ordinary Least Squares (OLS); 0.8/0.5/0.3 x OLS; or set as zero
- (p-value)*** 1% significance; (p-value)** 5% significance; (p-value)* 10% significance

Table 2. Changes in unconditional volatility

The table shows the results from an ARCH/GARCH variance regression for the total period. The mean equation [$y_t = a + by_{t-1} + \varepsilon_t$] generated the residuals for the variance equation, estimated by regressing the lognormal share-returns on the one-period lagged returns of each share. A variance equation [$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} + \delta D_F$] that includes a dummy variable produced the ARCH and GARCH terms as well as the coefficient δ which captures the change in the unconditional variance of the error terms pre to post SSF. The autoregressive root (α+β) governs the persistence of volatility shocks.

Company	δ	ω	ARCH (α)	GARCH (β)	α+β
1 AFE	-0.00001 (0.5472)	0.00006 (0.1943)	0.07607 (0.1081)	0.69049 (0.0002)***	0.76656
2 AFL	-0.00001 (0.6192)	0.00006 (0.1111)	0.05183 (0.0105)**	0.92147 (0.0000)***	0.97330
3 ALT	-0.00001 (0.4043)	0.00004 (0.3545)	0.06630 (0.0983)**	0.77885 (0.0001)***	0.84515
4 AMA	-0.00002 (0.3372)	0.00007 (0.2388)	0.04817 (0.1212)	0.76085 (0.0000)***	0.80902
5 APK	0.00003 (0.3850)	0.00008 (0.0334)**	0.14889 (0.1178)	0.60640 (0.0001)***	0.75528
6 ART	-0.00003 (0.4745)	0.00017 (0.0199)**	0.20011 (0.0288)**	0.40035 (0.0699)*	0.60046
7 BRC	-0.00018 (0.0228)**	0.00027 (0.0146)**	0.15900 (0.0179)**	0.38439 (0.0690)*	0.54339
8 CDZ	-0.00003 (0.2663)	0.000010 (0.1711)	0.06954 (0.0856)*	0.72567 (0.0000)***	0.79521
9 CPT	-0.00001	0.00003	0.08015	0.81803	0.89818

The table shows the results from an ARCH/GARCH variance regression for the total period. The mean equation [$y_t = a + by_{t-1} + \varepsilon_t$] generated the residuals for the variance equation, estimated by regressing the lognormal share-returns on the one-period lagged returns of each share. A variance equation [$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} + \delta D_F$] that includes a dummy variable produced the ARCH and GARCH terms as well as the coefficient δ which captures the change in the unconditional variance of the error terms pre to post SSF. The autoregressive root (α+β) governs the persistence of volatility shocks.

Company	δ	ω	ARCH (α)	GARCH (β)	α+β
	(0.4330)	(0.1021)	(0.0397)**	(0.0000)***	
10 CSB	-0.00001 (0.4816)	0.00004 (0.1309)	0.06966 (0.0596)*	0.79611 (0.0000)***	0.86577
11 DDT	-0.00002 (0.3575)	0.00005 (0.1170)	0.07052 (0.0056)***	0.89281 (0.0000)***	0.96333
12 DGC	0.00001 (0.9403)	0.000032 (0.0114)**	0.12950 (0.0222)**	0.45957 (0.0148)**	0.58906
13 DUR	0.00065 (0.1780)	0.00113 (0.0133)**	0.27638 (0.0201)**	0.29574 (0.2060)	0.57212
14 EOH	-0.00001 (0.4899)	0.00007 (0.0554)*	0.14641 (0.0175)**	0.49994 (0.0145)**	0.64635
15 ERM	0.00001 (0.0163)**	0.00001 (0.0001)***	0.01695 (0.0047)***	0.96450 (0.0000)***	0.98144
16 GDF	-0.00026 (0.1403)	0.00035 (0.1387)	0.06604 (0.0643)*	0.46080 (0.1676)	0.52685
17 GIJ	-0.00009 (0.4045)	0.00013 (0.3778)	0.15636 (0.0079)***	0.82033 (0.0000)***	0.97669
18 GND	0.00085 (0.0712)*	0.00005 (0.0201)**	0.40780 (0.0337)**	0.53942 (0.0000)***	0.94722
19 HDC	-0.00005 (0.0613)*	0.00011 (0.0472)**	0.13049 (0.0650)*	0.55015 (0.0059)***	0.68065
20 JCD	-0.00003 (0.4837)	0.00015 (0.0247)**	0.22152 (0.0007)***	0.66813 (0.0000)***	0.88965
21 JSC	-0.00004 (0.5035)	0.00018 (0.0356)**	0.17133 (0.0029)***	0.65005 (0.0000)***	0.82138
22 KAP	-0.00043 (0.0004)***	0.00064 (0.0000)***	0.23647 (0.0003)***	0.37506 (0.0003)***	0.61153
23 KGM	-0.00010 (0.0551)*	0.00015 (0.0499)**	0.08559 (0.0267)**	0.48963 (0.0330)**	0.57522
24 KWV	-0.00002 (0.0792)*	0.00005 (0.0793)*	0.02749 (0.0614)*	0.72282 (0.0000)***	0.75031
25 LBH	-0.00008 (0.1645)	0.00014 (0.1679)	0.06136 (0.0972)*	0.37163 (0.3817)	0.43299
26 LON	-0.00018 (0.2188)	0.00031 (0.2163)	0.07452 (0.1594)	0.49708 (0.1872)	0.57160
27 MCE	-0.00001 (0.6746)	0.00007 (0.0462)**	0.13303 (0.0032)***	0.82956 (0.0000)***	0.96259
28 OMN	-0.00011 (0.0004)***	0.000017 (0.0000)***	0.43150 (0.0000)***	0.30987 (0.0011)***	0.74137
29 PCN	-0.00019 (0.1937)	0.00036 (0.1063)	0.15167 (0.0346)**	0.59137 (0.0011)***	0.74304
30 PIM	-0.00007 (0.2494)	0.00022 (0.0469)**	0.13033 (0.0067)***	0.77662 (0.0000)***	0.90695
31 PWK	0.0000004 (0.6454)	0.00003 (0.0878)*	0.07983 (0.0387)**	0.72028 (0.0000)***	0.80011
32 SGG	0.00007 (0.6587)	0.00048 (0.0953)*	0.25747 (0.0969)*	0.45965 (0.0694)*	0.71712
33 SHP	-0.000003 (0.8694)	0.00007 (0.0762)*	0.15810 (0.0286)**	0.64155 (0.0000)***	0.79965
34 SIM	-0.00033 (0.4116)	0.00038 (0.3901)	0.09304 (0.0102)**	0.84886 (0.0000)***	0.94190
35 SLM	-0.00020 (0.1010)	0.00034 (0.0594)*	0.27638 (0.0297)**	0.36804 (0.1488)	0.64443

The table shows the results from an ARCH/GARCH variance regression for the total period. The mean equation [$y_t = a + by_{t-1} + \varepsilon_t$] generated the residuals for the variance equation, estimated by regressing the lognormal share-returns on the one-period lagged returns of each share. A variance equation [$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} + \delta D_F$] that includes a dummy variable produced the ARCH and GARCH terms as well as the coefficient δ which captures the change in the unconditional variance of the error terms pre to post SSF. The autoregressive root (α+β) governs the persistence of volatility shocks.

Company	**δ**	**ω**	**ARCH (α)**	**GARCH (β)**	**α+β**
36 SPG	-0.00006 (0.0896)*	0.000014 (0.0161)**	0.23719 (0.0319)**	0.41794 (0.0153)**	0.65513
37 UCS	-0.00001 (0.7299)	0.00018 (0.0262)**	0.16186 (0.0033)***	0.56037 (0.0001)***	0.72223
38 WNH	-0.00017 (0.0356)**	0.00031 (0.0147)**	0.16846 (0.0153)**	0.52051 (0.0008)***	0.68897

Notes:
- Default: Normal (Gaussian) error distribution with OLS starting values
- Alternative distributions: Student's t (optional fixed degrees of freedom) and GED (optional fixed parameter)
- Starting coefficients generated with Ordinary Least Squares (OLS); 0.8/0.5/0.3 x OLS; or set as zero
- (p-value)*** 1% significance; (p-value)** 5% significance; (p-value)* 10% significance

Figure 3. Changes in volatility, ARCH and GARCH

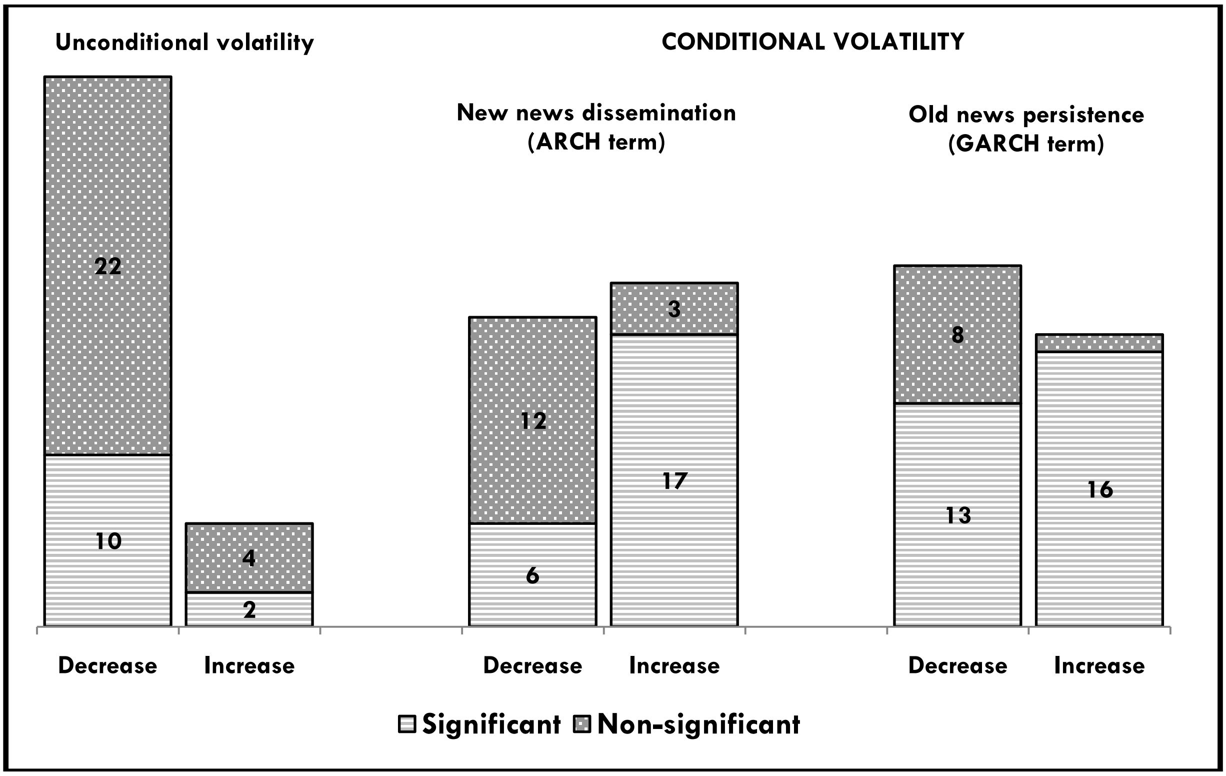


Table 3. Summary of ARCH/GARCH model results

The table shows the per company change in spot volatility, change in the speed at which new information is incorporated in the share price (ARCH effect), and change in the influence of past news on the current share price (GARCH effect). A change in the autoregressive root (ARCH plus GARCH effect) represents a change in the persistence of shocks on the share price, determined jointly by the rate of dissemination and lingering impact of news.

No	Code	σ	ARCH	GARCH	AR Root	No	Code	σ	ARCH	GARCH	AR Root
1	AFE	–	+	–	–	20	JCD	–	+	–	–
2	AFL	–	+	–	–	21	JSC	–	–	+	+
3	ALT	–	+	+	+	22	KAP	–	–	+	–
4	AMA	–	+	–	+	23	KGM	–	+	+	+
5	APK	+	+	–	–	24	KWV	–	–	+	+
6	ART	–	+	+	+	25	LBH	–	–	–	–
7	BRC	–	+	+	+	26	LON	–	–	+	+
8	CDZ	–	+	–	–	27	MCE	–	–	+	+
9	CPT	–	+	–	–	28	OMN	–	+	–	+
10	CSB	–	+	+	+	29	PCN	–	–	+	+
11	DDT	–	–	+	+	30	PIM	–	+	–	–
12	DGC	+	–	–	–	31	PWK	+	+	–	–
13	DUR	+	–	+	+	32	SGG	–	–	–	–
14	EOH	–	+	–	+	33	SHP	–	+	–	–
15	ERM	+	+	–	–	34	SIM	–	–	+	+
16	GDF	–	–	+	+	35	SLM	–	–	+	–
17	GIJ	–	–	+	–	36	SPG	–	–	–	–
18	GND	+	+	–	–	37	UCS	–	–	–	–
19	HDC	–	–	–	–	38	WNH	–	+	–	+

Statistically significant change

Spot volatility				Dissemination rate				Long-term impact				Persistence of shocks	
Decrease		Increase		Decrease		Increase		Decrease		Increase		Decrease	Increase
32		6		18		20		21		17		20	18
s	ns	s	ns	s	ns	s	ns	s	ns	s	ns		
10	22	2	4	6	12	17	3	13	8	16	1		

The majority (32) of companies showed a decline in spot volatility following the onset of futures trading. Only ten (10) shares exhibited a statistically significant decline in volatility.

The majority (20) of companies showed an increase in the speed at which new information is incorporated in the price, seventeen (17) at a statistically significant level.

The majority (21) of companies showed a decrease in the durability of disseminated news. Thirteen (13) shares revealed a statistically significant decline in the role played by old news in establishing the price.

The majority (20) of companies displayed a diminished propensity to shocks influencing the share price.

Appendix A. Industry and trading date information

N	INDUSTRY (abbreviation): Supersector – Sector – Subsector		Introduction	Trade date
	BASIC MATERIALS (BM)			
	Basic Resources – Mining – Gold Mining			
2	AFLQ	The Afrikander Lease Limited	06/02/2003	10/02/2003

N	INDUSTRY (abbreviation): Supersector – Sector – Subsector		Introduction	Trade date
13	DURQ	Durban Roodepoort Deep	07/11/2001	08/11/2001
20	JCDQ	JCI Limited	13/08/2003	14/08/2003
34	SIMQ	Simmer and Jack Mines Limited	09/01/2006	09/01/2006
	Basic Resources – Mining – Platinum & Precious Metals			
26	LONQ	Lonmin PLC	19/11/2003	19/11/2003
	Chemicals – Chemicals – Speciality Chemicals			
1	AFEQ	AECI Limited	28/06/2004	13/07/2004
28	OMNQ	Omnia Holdings Limited	22/07/2003	22/07/2003
	CONSUMER GOODS (CG)			
	Food & Beverage – Beverages – Distillers & Vintners			
24	KWVQ	KWV Investments Limited	14/11/2006	14/11/2006
	Personal & Household Goods – Leisure Goods – Consumer Electronics			
4	AMAQ	Amalgamated Appliance Holdings Limited	05/07/2005	06/07/2005
	CONSUMER SERVICES (CS)			
	Media – Media – Broadcasting & Entertainment			
23	KGMQ	Kagiso Media Limited	13/05/2005	13/05/2005
	Retail – Food & Drug Retailers – Food Retailers & Wholesalers			
31	PWKQ	Pick and Pay Holdings Limited	16/04/2005	19/04/2005
33	SHPQ	Shoprite Holdings Limited	28/11/2002	28/11/2002
	Retail – General Retailers – Broadline Retailers			
7	BRCQ	Brandcorp Holdings Limited	22/11/2004	23/11/2004
	Retail – General Retailers – Home Improvement Retailers			
10	CSBQ	Cashbuild Limited	22/02/2005	23/02/2005
	Travel & Leisure – Travel & Leisure – Gambling			
16	GDFQ	Gold Reef Casinos Resorts Limited	02/06/2004	04/06/2004
	FINANCIALS (F)			
	Financial Services – General Financial – Investment Services			
8	CDZQ	Cadiz Holdings Limited	03/08/2005	04/08/2005
	Financial Services – General Financial – Speciality Finance			
15	ERMQ	Enterprise Risk Management Limited	04/10/2005	06/10/2005
	Insurance – Life Insurance – Life Insurance			
9	CPTQ	Capital Alliance Holdings Limited	17/09/2003	17/09/2003
25	LBHQ	Liberty Holdings Limited	06/10/2003	06/10/2003
32	SGGQ	Sage Group Limited	21/01/2004	23/01/2004
35	SLMQ	Sanlam	21/07/2000	03/08/2000
	INDUSTRIALS (I)			
	Industrial Goods & Services – Electronic & Electrical Equipment – Electrical Components & Equipment			
21	JSCQ	Jasco Electronics Holdings	23/01/2006	23/01/2006

N	INDUSTRY (abbreviation): Supersector – Sector – Subsector		Introduction	Trade date
	Industrial Goods & Services – Electronic & Electrical Equipment – Electronic Equipment			
12	DGCQ	Digicore Holdings Limited	22/08/2005	22/08/2005
	Industrial Goods & Services – General Industrials – Containers & Packaging			
5	APKQ	Astrapak Limited	19/08/2004	19/08/2004
	Industrial Goods & Services – General Industrials – Diversified Industrials			
6	ARTQ	Argent Industrial Limited	22/09/2004	27/09/2004
22	KAPQ	KAP International Holdings	18/01/2005	28/01/2005
	Industrial Goods & Services – Industrial Engineering – Industrial Machinery			
19	HDCQ	Hudaco Industries Limited	04/04/2005	04/04/2005
	Industrial Goods & Services – Industrial Transportation – Marine Transportation			
18	GNDQ	Grindrod Limited	24/03/2004	24/03/2004
	Industrial Goods & Services – Industrial Transportation – Trucking			
36	SPGQ	Super Group Limited	26/02/2004	26/02/2004
	Industrial Goods & Services – Support Services – Industrial Suppliers			
38	WNHQ	Winhold Limited	14/08/2006	14/08/2006
	TECHNOLOGY (T)			
	Technology – Software & Computer Services – Computer Services			
11	DDTQ	Dimension Data Holdings Limited	08/02/1999	08/02/1999
14	EOHQ	EOH Holdings Limited	07/02/2006	10/02/2006
17	GIJQ	Gijima AST Group Limited	12/09/2005	13/09/2005
29	PCNQ	Paracon Holdings Limited	23/11/2005	23/11/2005
	Technology – Software & Computer Services – Software			
30	PIMQ	Prism Holdings Limited	10/11/2004	10/11/2004
37	UCSQ	UCS Group Limited	14/12/2005	14/12/2005
	Technology – Technology Hardware & Equipment – Computer Hardware			
3	ALTQ	Allied Technologies Limited	21/05/2003	22/05/2003
	TELECOMMUNICATIONS (TC)			
	Telecommunications – Mobile Telecommunications – Mobile Telecommunications			
27	MCEQ	M-Cell Limited	08/08/2000	22/08/2000

Source: JSE Limited (2005)