

---

# Existence and extent of impact of individual stock derivatives on spot market volatility in India

Abhilash S. Nair

*Indian Institute of Management, Kozhikode 673 570, Kerala, India*

*E-mail: abhilash@iimk.ac.in; abhilash\_n\_2000@yahoo.com*

---

This article first examines the existence of a change in the structure of conditional volatility of stock returns around the time when trading in individual stock derivatives is introduced. Thereafter, it analyses the extent of the structural change between the pre- and post-derivatives regimes, after allowing for asymmetric response to ‘good’ and ‘bad’ news, following the Generalized Autoregressive Conditional Heteroscedastic (GARCH) family of models. Since the exact point of regime change is known for each stock analysed, the article specifies alternative switching asymmetric GARCH (Exponential GARCH (EGARCH), Periodic GARCH (PGARCH) and Glosten–Jagannathan–Runkle GARCH (GJR GARCH)) models for each stock. The final choice of model is made on the basis of the news impact curve. The main finding of this study is that although derivatives seem to enhance the quantity of information transmitted to the spot market, the quality of such information is doubtful, resulting in delayed incorporation of such information into price. This, the article argues, may be because trading volumes in the Indian derivatives market are dominated by retail investors who lack access to information relevant for trading in the short run. The article then builds a case for introducing longer term derivative instruments for more meaningful retail participation.

## **I. Introduction**

The introduction of derivative trading in an asset is expected to attract market players who tend to increase the spot market information efficiency. These market players can be of three types: (i) hedgers, (ii) arbitrageurs and (iii) speculators. Further, speculators can be either (completely) informed or partially informed. Since the investment required to buy the derivative instrument is much lesser than buying the underlying asset, hedgers may find derivatives to be a cheaper mode of hedging their spot market exposure. Speculators find the

derivatives market attractive because they could trade in more units of underlying asset for the same investment. Arbitrageurs thrive on mispricing. They remove mispricing in both, the spot and the derivative market, thus linking the asset price in the two markets and in the process making risk-free gains.

Hedgers, arbitrageurs and informed speculators transmit new information into the spot market by taking trading positions in the derivatives market. Since the asset under discussion is the stock of a company, it is well established in prior research that its return volatility changes with time (Mandelbrot, 1963; Fama, 1965) and is conditional on ‘old’ and

'new' information. In theory, introduction of derivatives trading is expected to change the structure of conditional volatility by reducing the impact of 'old' information and increasing the rate at which 'new' information is incorporated. Derivatives thus result in greater information efficiency and lower conditional volatility in the spot market. However, in the presence of the partially informed speculators, the gains from trading in derivatives would diminish, because trades by the less informed speculators produce noise. Such noise, if transmitted to the spot market does not result in increased information efficiency and reduced conditional volatility.

In India, 'securities'-based derivative trading started in June 2000, first on index and then on individual stocks. As in other markets, the idea in India was that derivatives would increase the information efficiency in the spot market and thus reduce conditional volatility. However, this idea may not hold in the presence of partially informed traders. Hence, after a decade of introduction of trading in individual stock derivatives, it is important to examine its impact on the conditional stock return volatility in the spot market. The aim of this article is to test the existence and extent of the change in structure of conditional volatility of the stock as derivatives are introduced.

This article contributes to the existing empirical literature in a number of ways. First, it illustrates the application of wavelet variance analysis, a more robust approach, to test the existence of change in structure of conditional volatility (Fernandez, 2006). Second, several prior papers assume the response of conditional volatility to 'good' and 'bad' news as symmetric. In the case of stock returns, it is well established that its return volatility would respond more to 'bad' news as compared to 'good' news (Black, 1976; Christie, 1982; Pindyk, 1984; French *et al.*, 1987). To account for this finding, this article specifies appropriate asymmetric Generalized Autoregressive Conditional Heteroscedastic (GARCH) models, for each stock in the sample. The final choice of model is based on the response of conditional volatility to 'new' information as captured by the News Impact Curve (NIC). Third, most prior papers examine the change in structure of conditional volatility by comparing the GARCH coefficients estimated in the pre- and post-derivatives regimes; they do so by making strong distributional assumptions about asset returns in the two regimes. To analyse the structural change in a more general setting and given that the exact point of regime change is known in the case of each stock, this article adopts a Switching Asymmetric GARCH (SAGARCH) specification to model conditional volatility.

The SAGARCH specifications incorporate the interaction of slope and intercept dummies with the respective parameters of the conditional variance equation. The dummy takes a value zero pre-introduction and one post-introduction of derivatives trading, thus capturing the change in each parameter, across the two regimes. Finally, to the best of my knowledge, this is the most comprehensive (101 stocks) examination to date of the impact of trading in stock derivatives on the conditional volatility of the underlying stock in the Indian context.

The study finds that after trading in derivatives commenced, the information flow to spot market rose for most stocks included in the article. As a result, there seems to be a reduction in the impact of 'old' information on conditional volatility. However, this reduction is not due to an increase in the rate at which 'new' information is being impounded into spot prices. This may be because most of the volumes in the Indian derivatives market originate from retail investors who lack access to information relevant for trading in the short run. Thus, although there seems to be an increase in 'new' information emanating from derivatives market, the reliability of this information is in question resulting in delayed incorporation of this news in spot asset price. From a policy perspective, it may be argued that introduction of longer term derivative instruments (for periods more than 3 months) would attract more meaningful retail participation, thus reducing the proportion of noise traders in the derivatives market. This policy recommendation is in conformity with the views expressed in the report of the derivative market review committee, set up by Securities Exchange Board of India (2008), that 'longer expiration dates offer the opportunity for longer-term investors to take a view on the price changes without combinations of shorter-term options contract'.

The article is organized as follows: Section II reviews relevant literature and presents gaps in research. Section III elaborates the empirical design of the article. Section IV describes the data and discusses the results and Section V concludes this article.

## II. Review of Literature

Ever since the introduction of derivative contracts on financial assets in the early 1980s, there have been a number of studies that examine its impact on the spot market. However, most of these studies have analysed the introduction of index futures (Antoniou and Holmes, 1995; Antoniou *et al.*, 1998; Butterworth,

2000; Gulen and Mayhew, 2000; Bologna and Cavallo, 2002; Bandivadekar and Ghosh, 2003; Shenbagaraman, 2003). Several papers, which study the impact of individual stock derivative trading on the return volatility of the underlying stock either consider a small sample (Nath, 2003; Vipul, 2006) or are limited to examining the introduction of individual stock futures (Dennis and Sim, 1999).

To highlight the contribution of this article, I classify the existing literature into three categories based on the limitations in these papers that are addressed by my article. First, the introduction of trading in individual stock derivative instruments is expected to change the structure of conditional return volatility. However, before one attributes the structural change to introduction of derivatives trading, it is necessary to check for the existence of such a change (in structure of conditional volatility) around the time when derivatives trading is introduced. Prior studies often do not conduct this test (Antoniou *et al.*, 1998; Dennis and Sim, 1999; Butterworth, 2000; Gulen and Mayhew, 2000; Bologna and Cavallo, 2002; Bandivadekar and Ghosh, 2003; Nath, 2003; Shenbagaraman, 2003; Vipul, 2006). Even the few studies that test the existence of structural change in conditional volatility around the time when derivatives trading is introduced, do so by including an intercept dummy in the specification of conditional variance. If the dummy significantly explains conditional volatility, then it is concluded that there is a change in the structure (e.g. Antoniou and Holmes, 1995). However, two difficulties arise in this line of reasoning: (a) if the dummy is significant, it only means that the conditional volatility has changed and does not necessarily mean that there is a change in its structure, (b) if the dummy is insignificant, then it does not necessarily mean that there is no change in structure of conditional volatility. The structure may have changed in such a way that the level of conditional volatility would remain the same. Two alternative approaches to detect a possible structural change, after allowing for multiple breaks in structure, are the wavelet variance analysis approach and the Cumulative Sum of Squares (CUSUM) approach (Inclan and Tiao, 1994; Aggarwal *et al.*, 1999). However, Fernandez (2006) finds that the wavelet variance analysis gives superior results as compared to CUSUM estimates. Hence, in this study, a wavelet variance-based approach is adopted to confirm the existence of a change in structure of conditional stock return volatility around the time when derivatives trading is introduced in the said stock.

Second, the existence of asymmetric response of volatility to 'good' and 'bad' information has been extensively documented in the case of stock returns.

Two reasons put forth for the existence of such a phenomenon are: (i) Leverage Effect (Black, 1976; Christie, 1982): According to this explanation, a negative return shock leads to a fall in prices and therefore a rise in leverage. Consequently, as 'bad' news is incorporated, the perceived riskiness of the stock increases, thus resulting in a further fall in prices and a rise in stock return volatility, (ii) Volatility Feedback (Pindyk, 1984; French *et al.*, 1987; Campbell and Hentschel, 1992): According to this explanation, an expected increase in future volatility leads to higher expected return (as compensation to bear this risk) and thereby lowering the stock price. Consequently, one witnesses higher price volatility in response to 'bad' news as compared to 'good' news. The two explanations differ in their causal linkages. While leverage effect hypothesizes that current negative return shock causes higher future price volatility, volatility feedback effect hypothesizes that anticipated higher future volatility leads to current negative return shock. At the firm level, it is empirically well established that asymmetric response of volatility is primarily due to volatility feedback hypothesis (Bekaert and Wu, 2000). Volatility feedback or time varying expected return occurs because not all investors react in a rational manner (Antoniou *et al.*, 1998). Such behaviour is typical of market players (investors) who have lower access to information (noise traders). These investors react more strongly to 'bad' news than to 'good' news. If noise traders are the cause of asymmetry in the market, then introduction of derivatives market may attract the noise traders from the spot market.

Hence, before specifying the structure of conditional volatility, one must check whether the response of return volatility to 'good' and 'bad' news is symmetric. Especially, in the case of individual stocks, since unlike indexes, individual stocks are not diversified. As a result, the change in expected return, caused by the leverage effect or the volatility feedback effect, would be more pronounced in the case of individual stocks as compared to indexes.

To my knowledge, most papers studying the impact of derivatives on spot market return volatility do not test for asymmetric response (Antoniou and Holmes, 1995; Antoniou *et al.*, 1998; Bologna and Cavallo, 2002; Bandivadekar and Ghosh, 2003; Nath, 2003; Shenbagaraman, 2003; Pok and Poshakwale, 2004; Vipul, 2006). Even those studies that have examined the existence of asymmetric response, specify either GJGARCH (GJR GARCH) model (Butterworth, 2000; Gulen and Mayhew, 2000; Pilar and Rafael, 2002) or Exponential GARCH (EGARCH) model (Dennis and Sim, 1999) without testing which

specification best captures the asymmetric response. This article overcomes this limitation by specifying the asymmetric GARCH model based on the response of volatility to ‘new’ information as captured in the NIC. The model, that best captures the volatility dynamics, asymmetric response and which gives minimum volatility in the absence of additional information, is chosen.

Finally, it appears that most prior studies examining this issue estimate conditional volatility for each regime (before and after introduction of derivatives trading) and then compare the estimated coefficients (e.g. Antoniou and Holmes, 1995; Antoniou *et al.*, 1998; Dennis and Sim, 1999; Butterworth, 2000; Gulen and Mayhew, 2000; Bologna and Cavallo, 2002; Nath, 2003; Pok and Poshakvale, 2004; Ryoo and Smith, 2004; Vipul, 2006). Such a comparison can only establish whether the two sets of coefficients are statistically different or not. It may not be appropriate to compare the magnitude of their impact on the conditional volatility in each regime because the information set embedded (in each regime) is different. This study overcomes this problem by specifying a SAGARCH model which tests for a change in structure of conditional volatility, in more general settings. The SAGARCH model allows slope and intercept dummies to interact with respective parameters of conditional volatility (Lee and Ohk, 1992).

In summary, this article adds to the existing literature first by analysing the impact of introduction of derivative instruments (both futures and options) in individual stocks on the return volatility of the underlying stock and second, by examining a large sample of 101 stocks on which both futures and options instruments are available. Finally, the study attempts to overcome the shortcomings of existing research in this field by testing for existence of structural break following the wavelet variance analysis approach and by specifying the appropriate SAGARCH model based on the NIC for each model.

### III. Empirical Design

#### *Existence of change in the structure of conditional volatility*

**Wavelet variance analysis.** In order to test the existence of a structural change in spot market volatility around the time of introduction of derivatives trading, this article adopts the wavelet variance analysis approach. To conduct wavelet variance analysis, one needs to first make a Discrete Wavelet

Transform (DWT), of the underlying series. Wavelet variance analysis partitions the variance of a given time series into pieces that are associated to different time scales. This will help us identify the time scales that are important contributors to variability of a series. Say  $\sigma_x^2$  is the variance of a stationary time series  $x$ . If  $v_x^2(\tau_j)$  denotes the wavelet variance at scale  $\tau_j = 2^{j-1}$ , then the following relationship should hold:  $\sigma_x^2 = \sum_{j=1}^{\infty} v_x^2(\tau_j)$ .

**Discrete wavelet transform.** A DWT allows decomposition of the given time series into high- and low-frequency components. The low-frequency components (father wavelets denoted as  $\phi$ , from here on) describe the smooth baseline trend of the series. Whereas, high-frequency components (mother wavelets, denoted as  $\psi$ , from here on) represents the detailed parts for each time scale by noting the amount of stretching of the wavelet such that:  $\int_t \phi(t)dt = 1$  and  $\int_t \psi(t)dt = 0$ .

Most applications of wavelets in economics and finance assume orthogonal wavelets. The orthogonal wavelet series approximation of a continuous signal  $f(t)$  is given by

$$f(t) \approx \sum_k s_{jk} \phi_{jk}(t) + \sum_k d_{jk} \psi_{jk}(t) + \sum d_{j-1,k} \psi_{j-1k}(t) + \dots + \sum_k d_{1k} \psi_{1k}(t) \quad (1)$$

where,  $j$  is the number of scales into which the time series is broken and  $k$  represents the number of coefficients in the corresponding time scale. For instance, when one is analysing daily data, the wavelet scales are such that scale one is associated with 2–4 day dynamics, scale two with 4–8, scale three with 8–16 and so on. In the above equation  $s_{jk}$ ,  $d_{jk}, \dots, d_{1k}$  are the wavelet transform coefficients where  $d_{1k}$  is the finest scale obtained when the length of the data is divided by  $2^j$  producing  $n/2^j$  coefficients. At the next finest scale,  $d_{2k}$ , there are  $n/2^{2j}$  coefficients. Similarly, at the coarsest scale, there are  $n/2^j$  coefficients, each for  $d_{jk}$  and  $s_{jk}$ . The number of coefficients at each scale is related to the width of the wavelet function. In Equation 1,  $\phi_{jk}(t)$  and  $\psi_{jk}(t)$  are the approximating wavelet functions given as

$$\phi_{jk}(t) = 2^{-j/2} \phi\left(\frac{t - 2^j k}{2^j}\right), \quad \psi_{jk}(t) = 2^{-j/2} \psi\left(\frac{t - 2^j k}{2^j}\right) \quad (2)$$

The wavelet coefficients  $s_{jk}$  and  $d_{jk}$  can be approximated as

$$s_{jk} \approx \int \phi_{jk}(t) f(t) dt, \quad d_{jk} \approx \int \psi_{jk}(t) f(t) dt$$

**Test for structural change.** For a given time series, let  $n'_j = n/2^j$  be the number of DWT coefficients at level  $j$  and let  $L'_j \equiv (L-2)(1-2^{-j})$  be the number of DWT boundary coefficients at level  $j$  ( $n'_j > L'_j$ ) where  $L$  is the width of the wavelet filter. An unbiased estimate of the variance is given by

$$v_x^2(\tau_j) \equiv \frac{1}{(n'_j - L'_j)2^j} \sum_{t=L'_j-1}^{n'_j-1} d_{jt}^2 \quad (3)$$

As stated earlier, most applications of wavelets in finance and economics assume orthogonal wavelets in order to ensure that the results obtained from a wavelet transform are uncorrelated. Hence, to test for existence of structural change, one tests whether the DWT coefficients  $d$ , for scale  $j$ , at time  $t$ , follow a zero mean Gaussian white noise process. The  $D$ -statistic, which is based on normalized CUSUM of the DWT coefficients, denotes the maximum deviation of  $d_{jt}$  from a hypothetical linear cumulative energy trend. This  $D$ -statistic is then compared to the critical value of  $D$ , testing a null hypothesis of absence of any structural change in variance (Percival and Walden, 2000).

#### *Extent of the change in the structure of conditional volatility*

On confirming the existence of a structural change in volatility around the time of introduction of derivatives trading, analysis of the extent of impact of this event on the structure of volatility is carried out. Since, the underlying asset being analysed is a stock, the probability of the series being characterized by heteroscedasticity is very high (Mandelbrot, 1963; Fama, 1965). In this study, after confirming the presence of Autoregressive Conditional Heteroscedastic (ARCH) effects, it is hypothesized that the conditional variance of the stock return series follows a GARCH process.

The standard GARCH ( $p, q$ ) model introduced by Bollerslev (1986) suggests that conditional variance of asset returns is a linear function of lagged conditional variance and past squared error terms. In this article, in order to filter any predictability associated with market pervasive factors as well as with lagged stock returns, the conditional mean returns equation includes an autoregressive term as well as the return on market portfolio. In the Indian market, since most of the trading takes place in the top 50 stocks,

National Stock Exchange Fifty (NSE Nifty) was chosen as a proxy for the market portfolio.

The conditional mean equation can now be represented as

$$\left. \begin{aligned} \text{Mean equation: } R_t &= c + \theta_1 R_{t-1} + \theta_2 R_{\text{nifty},t} + \varepsilon_t, \\ \text{where, } \varepsilon_t | \psi_{t-1} &\sim N(0, h_t) \\ \text{and conditional volatility equation:} \\ h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} \end{aligned} \right\} \quad (4)$$

where,  $R_t$  is the log returns of the underlying asset,  $\theta_1$  the impact of one period lagged returns on current returns,  $\theta_2$  depicts the effect of return on market portfolio on asset returns. Standardized  $\varepsilon_t$ , say  $e_t = \frac{\varepsilon_t}{\sqrt{h_t}}$ , is assumed to be independent and identically distributed (i.i.d.) with mean zero and unit variance  $h_t$  represents conditional variance of  $\varepsilon_t$  which varies over time for some nonnegative function,  $\alpha_1$  describes the 'news coefficient' (impact of one time period 'old' information) and  $\alpha_2$  represents the 'persistence coefficient' (impact of news older than one time period).<sup>1</sup>

Equation 4 is the standard GARCH (1, 1) model which assumes that the response of volatility, to 'bad' news as well as 'good' news, is symmetric. However, as stated earlier, this may not be the case always, especially while analysing individual stock returns. Three important variants of the GARCH family (Zivot, 2009), capable of capturing the said asymmetry in response of volatility to 'new' information, are EGARCH model proposed by Nelson (1991), the GJR GARCH model proposed by Glosten *et al.* (1993) and the Power GARCH (PGARCH) model proposed by Ding *et al.* (1993). Choice of the model, that best captures the asymmetric response of volatility, is made on the basis of the NIC for each model (Pagan and Schwert, 1990; Engle and Ng, 1993). NIC is the relationship between the conditional variance at time ' $t$ ' and the shock (error) term at time ' $t-1$ ', holding constant information dated ' $t-2$ ' and earlier, and with all lagged conditional variance evaluated at the level of the unconditional variance. Though, most of what is proposed above exists in literature, the contribution of this study is in the synthesis of the switching GARCH (1, 1) model with asymmetric response model and a lucid presentation of the equations for conditional variance, unconditional variance and NIC for EGARCH (1, 1), GJR GARCH (1, 1) and PGARCH (1, 1) models.

<sup>1</sup> Though in standard GARCH literature, persistence is understood as  $\alpha_1 + \alpha_2$  (Bollerslev, 1986), Antoniou and Holmes (1995) use the term to indicate the effect of past conditional variance on present conditional variance. This article refers to persistence as in Antoniou and Holmes (1995).

**Switching EGARCH (1,1).** Since the switching point is known, the EGARCH model (Nelson, 1991) can be extended to incorporate the change in regime. The conditional variance of a such a switching EGARCH (1,1) model is given by

$$h_t = \text{Exp} \left\{ (\alpha_0 + \beta_0 D) + (\alpha_1 + \beta_1 D) \left[ \frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] + (\alpha_2 + \beta_2 D) \ln(h_{t-1}) + (\gamma_1 + \gamma_2 D) \left[ \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right] \right\} \quad (5)$$

where  $h_t = \sigma_t^2$ ,  $\varepsilon_{t-1}$  is the error term in the mean Equation 4,  $\alpha_0 = \alpha_{0\text{pre}}(1 - D)$ ,  $\alpha_{0\text{pre}}$  is the EGARCH (1,1) intercept prior to introduction of derivatives,  $\beta_0 = \alpha_{0\text{post}}$  is the EGARCH intercept post introduction of derivatives.

Similarly,  $\alpha_1 = \alpha_{1\text{pre}}(1 - D)$ ,  $\alpha_2 = \alpha_{2\text{pre}}(1 - D)$  and  $\beta_1 = \alpha_{1\text{post}}$ ,  $\beta_2 = \alpha_{2\text{post}}$ ,  $\gamma_1 = \gamma_{1\text{pre}}(1 - D)$ ,  $\gamma_2 = \gamma_{2\text{post}}$  represent the ‘news’, ‘persistence’ and ‘asymmetric response’ coefficients, respectively, for the two regimes.  $D$  is a dummy variable that assumes a value zero before introduction of derivatives trading and one after introduction. It is expected that  $\gamma_1$  and  $\gamma_2$  will be negative, such that ‘bad’ news will have a much larger impact on volatility.

When  $\varepsilon_{t-1}$  is positive or there is a ‘good’ news at time  $t - 1$ , the total effect of this news on  $h_t$  as per Equation 5 is given by (Kassimatis, 2002)

$$h_t = A \times \text{Exp} \left[ \frac{\gamma_1 + \gamma_2 D + (\alpha_2 + \beta_2 D)}{\sigma} \times \varepsilon_{T-1} \right] \quad \text{for } \varepsilon_{t-1} > 0$$

and when there is ‘bad’ news

$$h_t = A \times \text{Exp} \left[ \frac{\gamma_1 + \gamma_2 D - (\alpha_2 + \beta_2 D)}{\sigma} \times \varepsilon_{T-1} \right] \quad \text{for } \varepsilon_{t-1} < 0$$

where

$$A = \sigma^{2(\alpha_1 + \beta_1 D)} \times \text{Exp} \left[ (\alpha_0 + \beta_0 D) - (\alpha_1 + \beta_1 D) \sqrt{\frac{2}{\pi}} \right]$$

and  $\sigma^2$  is the unconditional volatility of a EGARCH (1,1) model given by

$$\sigma^2 = \text{Exp} \left[ \frac{\alpha_0 - \alpha_2 \left( \sqrt{\frac{2}{\pi}} \right)}{1 - \alpha_1} + \frac{1}{2} \left( \frac{\alpha_2^2 + \gamma_1^2}{1 - \alpha_1^2} \right) \right]$$

**Switching PGARCH (1,1,  $\delta$ ).** The PGARCH model (Ding *et al.*, 1993) can be extended to incorporate the

change in regime. The conditional variance of such a switching PGARCH (1,1, $\delta$ ) model is given by

$$h_t = \{ (\alpha_0 + \beta_0 D) + (\alpha_1 + \beta_1 D) \times [|\varepsilon_{t-1}| + (\gamma_1 + \gamma_2 D) \varepsilon_{t-1}]^{(\delta_1 + \delta_2 D)} + (\alpha_2 + \beta_2 D) \sigma^{(\delta_1 + \delta_2 D)} \}^{\frac{2}{(\delta_1 + \delta_2 D)}} \quad (6)$$

where  $\delta$  is a positive exponent and  $\gamma$  denotes the coefficient of asymmetric response,  $\alpha_0 = \alpha_{0\text{pre}}(1 - D)$ ,  $\alpha_{0\text{pre}}$  being the PGARCH intercept prior to the introduction of derivatives trading and  $\beta_0 = \alpha_{0\text{post}}$ , which is the PGARCH intercept post introduction of derivatives trading. Similarly,  $\alpha_1 = \alpha_{1\text{pre}}(1 - D)$ ,  $\beta_1 = \alpha_{1\text{post}}$ ,  $\alpha_2 = \alpha_{2\text{pre}}(1 - D)$ ,  $\beta_2 = \alpha_{2\text{post}}$ ,  $\gamma_1 = \gamma_{\text{pre}}(1 - D)$  and  $\gamma_2 = \gamma_{2\text{post}}$  are the ‘news’, ‘persistence’ and ‘asymmetric response’ coefficients, respectively, in the pre- and post-introduction period. The  $\delta_1$  and  $\delta_2$  are the power transformation parameters for the pre- and post-introduction period and  $D$  is a dummy variable that takes a value zero pre-introduction and one post-introduction of derivatives trading. It is expected that  $\gamma_1$  and  $\gamma_2$  will be negative, meaning that the ‘bad’ news would have more impact on volatility than ‘good’ news.

The PGARCH (1,1,1) NIC can now be represented as (Zivot, 2009)

$$h_t = A + 2\sqrt{A}(\alpha_1 + \beta_1 D) \times [|\varepsilon_{t-1}| + (\gamma_1 + \gamma_2 D) \varepsilon_{t-1}] + (\alpha_1 + \beta_1 D)^2 [|\varepsilon_{t-1}| + (\gamma_1 + \gamma_2 D) \varepsilon_{t-1}]^2$$

where  $A = [(\alpha_0 + \beta_0 D) + (\alpha_3 + \beta_3 D) \sigma]^2$  and  $\sigma^2$  is the unconditional variance given by

$$\sigma^2 = \frac{\alpha_0^2}{\left[ 1 - \alpha_1 \sqrt{\frac{2}{\pi}} - \alpha_2 \right]^2}$$

**Switching GJR GARCH (1,1).** Given the switching point, the GJR GARCH (1,1) model (Glosten *et al.*, 1993) can be extended to incorporate the change in regime. The conditional volatility for such a switching GJR GARCH(1,1) model is given by

$$h_t = (\alpha_0 + \beta_0 D) + (\alpha_1 + \beta_1 D) \varepsilon_{t-1}^2 + (\alpha_2 + \beta_2 D) h_{t-1} + (\gamma_1 + \gamma_2 D) S_{t-1} \varepsilon_{t-1}^2 \quad (7)$$

where  $S_{t-1}^- = 1$  if  $\varepsilon_{t-1} < 0$  otherwise  $S_{t-1}^- = 0$  and  $\alpha_3$  is the coefficient of asymmetric response,  $\alpha_0 = \alpha_{0\text{pre}}(1 - D)$ ,  $\alpha_{0\text{pre}}$  being the GJR GARCH intercept in the pre-introduction period.  $\beta_0 = \alpha_{0\text{post}}$ , which is the GJR GARCH intercept in the post-introduction regime. And  $\alpha_1 = \alpha_{1\text{pre}}(1 - D)$ ,  $\beta_1 = \alpha_{1\text{post}}$ ,  $\alpha_2 = \alpha_{2\text{pre}}(1 - D)$ ,  $\beta_2 = \alpha_{2\text{post}}$ ,  $\gamma_1 = \gamma_{1\text{pre}}(1 - D)$ ,  $\gamma_2 = \gamma_{2\text{post}}$  are the ‘news’, ‘persistence’

and ‘asymmetric response’ coefficients in the pre- and post-derivatives regimes and  $D$  is a dummy variable that takes the value zero pre-introduction of derivatives trading and one post-introduction.

The NIC for a switching GJR GARCH (1, 1) is given by (Henry, 1998)

$$\sigma_t^2 = [(\alpha_0 + \beta_0 D) + (\alpha_2 + \beta_2 D)\sigma^2] + [(\alpha_1 + \beta_1 D) + (\gamma_1 + \gamma_2 D)(\varepsilon_{t-1} < 0)]\varepsilon_{t-1}^2$$

where,  $\sigma^2$  is the unconditional variance given by  $\sigma^2 = \alpha_0 / (1 - \alpha_1 - \alpha_2 - 0.5\gamma_1)$ .

**Test of goodness-of-fit for each specification.** In order to test the goodness-of-fit of the switching asymmetric GARCH (1, 1) specification, the squared standardized residuals of the model are tested for existence of autocorrelation following the Ljung Box (LB) test. The null hypothesis is nonexistence of autocorrelation. However, Burns (2002) finds the robustness of this test to be very poor, especially when trying to ascertain adequacy of a GARCH specification. He suggests a rank equivalent of the LB test and recommends it over the normal LB test, especially while evaluating the adequacy of GARCH models. In this study, both the LB Test for Squared Standardized Residuals (LBTSSR) as well as its rank equivalent is reported (Rank LBTSSR). However, for inferential purposes, only the Rank LBTSSR is used. All computations were done in R. For ease of understanding and in the interest of further research, the code used for the SAGARCH (1,1) analysis is given in Appendix 3.

#### IV. Data, Empirical Results and Discussion

##### Data

The sample consists of all those stocks which meet two criteria (i) derivative trading commenced on or before 31 March 2008 and (ii) there exist at least 2 years of data prior to the introduction of derivatives trading. The study analyses daily closing prices of each stock as well as Nifty index for the period January 1997 to June 2010. The data starts from 1 January 1997 or the day on which the company is listed on a stock exchange, whichever is later. Based on the above criteria, 101 companies are included in the sample. To filter the effect of market pervasive factors on stock return volatility, return on NSE Nifty Index was incorporated in the mean equation. The daily closing stock prices for each stock analysed as well as closing values of Nifty was obtained from Centre for Monitoring Indian Economy (CMIE)

database. The study analyses daily log returns for each stock in the sample.

##### Results

Table 1 reports the descriptive statistics for the log returns of each stock that is analysed. The table reports skewness, kurtosis, the Jarque–Bera (JB) test statistic (which examines the normality of the data) and the Lagrange Multiplier (LM) test (up to a lag of 12) of existence of heteroscedasticity by examining the presence of autocorrelation in squared residuals (Engle, 1982). The results indicate that the log returns series is mostly positively skewed and leptokurtic, thus violating the assumption of normal distribution. This result is further confirmed by the JB test, which finds that the return, on all the stocks in the sample, is not normally distributed. The results of the LM test reveal that, in the case of all but three stocks, the squared return series was found to be auto correlated. This hints a significant nonlinear temporal dependence and suggests that volatility may be following one of the ARCH-type processes. In summary, based on descriptive statistics, in all the stocks analysed, return volatility seems conditional and it changes over time.

Before proceeding to model, the structure of conditional volatility in the pre- and post-derivative trading regimes, this article examines whether there exists a structural change around the time of introduction of derivatives trading following the wavelet variance analysis approach. This approach tells us the frequency at which there exist break points (discontinuity) in the conditional volatility series. The null hypothesis is that the variance is homogenous at each time scale (lower time scales such as d1, d2 and d3 and higher time scales such as d5, d6 and d7). The lower and higher time scales indicate short- and long-term volatility dynamics, respectively. The pattern of volatility break points in the pre- and post-derivatives trading regimes is compared to examine possible change in structure of stock return volatility around the time when derivatives trading is introduced on the underlying stock.

As reported in Table 2 (and summarized in Fig. 1), about 75% of the stocks experienced some change in the pattern of volatility between the two regimes. In the case of 28 companies’ stocks, volatility is found to be dynamic in short term in the pre-derivatives regime, while in the post-derivatives regime, volatility is seen to be dynamic in both the short as well as long term. In the case of 48 companies’ stocks, volatility is seen to be dynamic in the short as well as long term in the pre-derivatives regime while it is dynamic only in the short term in the post-derivative regime. In the

Table 1. Summary statistics of stock returns

Company	Skewness	Kurtosis	JB	ARCH test
ABB Ltd.	-0.0784	8.274	3851.09***	169.93***
ACC Ltd.	-0.1261	5.702	1019.31***	251.59***
Aban Offshore Ltd.	0.1052	6.312	1445.94***	342.99***
Aditya Birla Nuvo Ltd.	-4.7244	129.593	2229264.48***	3.85
Alok Industries Ltd.	0.1824	6.254	1325.71***	322.17***
Alstom Projects India Ltd.	0.3008	5.417	654.64***	106.07***
Ambuja Cements Ltd.	0.0224	5.296	729.43***	330.17***
Arvind Ltd.	0.1385	6.871	2083.53***	356.8***
Aurobindo Pharma Ltd.	0.0670	7.063	2148.69***	283.44***
BEML Ltd.	0.4729	6.204	1527.23***	358.95***
Ballarpur Industries Ltd.	0.4625	5.853	1237.43***	251.87***
Balrampur Chini Mills Ltd.	0.2008	6.041	1270.42***	343.86***
Bank of Baroda	0.0851	6.661	1835.29***	514.59***
Bank of India	0.0936	5.462	822.95***	288.27***
Bata India Ltd.	0.2336	6.747	1973.16***	288.79***
Bharat Forge Ltd.	0.1830	5.430	833.57***	276.95***
Bharat Heavy Electricals Ltd.	0.0029	6.327	1531.5***	274.42***
Bharat Petroleum Corporation Ltd.	0.0213	6.093	1322.29***	177.6***
Bharti Airtel Ltd.	0.3138	5.849	731.79***	121.3***
Birla Corporation Ltd.	0.1608	4.437	266.79***	329.75***
Bombay Dyeing & Manufacturing Company Ltd.	0.2615	6.071	1342.85***	371.66***
CESC Ltd.	0.4589	5.564	997.21***	179.25***
Century Textiles & Industries Ltd.	0.0052	5.116	619.36***	266.09***
Chambal Fertilizers & Chemicals Ltd.	0.2031	14.844	19416.97***	480.57***
Chennai Petroleum Corporation Ltd.	0.2307	7.942	3408.42***	313.3***
Cipla Ltd.	-0.0431	6.444	1641.83***	261.13***
Colgate-Palmolive (India) Ltd.	0.5739	7.669	3184.84***	114.43***
Corporation Bank	0.2015	6.408	1521.41***	214.24***
Crompton Greaves Ltd.	0.2480	4.780	472.24***	309.22***
Cummins India Ltd.	0.2906	5.728	1054.87***	100.11
Dabur India Ltd.	0.1100	6.467	1667.5***	274.98***
Dena Bank	0.3794	7.916	3393.3***	380.11***
Escorts Ltd.	0.1138	5.427	821.7***	261.8***
Federal Bank Ltd.	0.0130	7.286	2535.88***	381.78***
GTL Ltd.	-0.1930	7.431	2737.66***	731.64***
Glaxosmithkline Pharmaceuticals Ltd.	0.1646	6.418	1630.79***	259.41***
Grasim Industries Ltd.	-0.1079	6.885	2093.99***	246.48***
Great Eastern Shipping Company Ltd.	0.2105	5.905	1180.1***	285.56***
Gujarat Alkalies & Chemicals Ltd.	0.4946	5.880	1269.48***	264.14***
HDFC Bank Ltd.	0.2949	8.840	4765.73***	433.39***
Hero Honda Motors Ltd.	0.2977	5.544	942.95***	249.06***
Hindalco Industries Ltd.	-0.1094	6.812	2016.38***	601.43***
Hindustan Construction Company Ltd.	0.2585	6.294	1498.43***	228.55***
Hindustan Petroleum Corporation Ltd.	-0.0786	9.064	5090.24***	106.26***
Hindustan Unilever Ltd.	0.1001	6.155	1383.75***	231.99***
Hotel Leelaventure Ltd.	0.4836	6.198	1544.09***	203.84***
Housing Development Finance Corporation Ltd.	0.3974	6.749	2032.01***	330.41***
ICICI Bank Ltd.	0.0700	6.109	1267.59***	457.93***
IFCI Ltd.	0.4760	8.153	3797.95***	199.09***
ITC Ltd.	0.0923	5.616	951.49***	301.28***
IVRCL Infrastructures & Projects Ltd.	-0.1733	8.395	3135.74***	322.17***
India Cements Ltd.	0.1203	5.178	654.67***	265.48***
Indian Hotels Company Ltd.	-0.1485	8.096	3605.16***	294.68***
Indian Overseas Bank	-0.1266	7.468	1955.55***	302.01***
Indusind Bank Ltd.	0.1583	5.327	702.96***	296.9***
Infosys Technologies Ltd.	-0.3505	9.164	5323.88***	316.8***
JSW Steel Ltd.	0.6586	7.669	3232.62***	229.04***
Jammu & Kashmir Bank Ltd.	0.3959	6.217	1305.73***	179.41***
Jindal Steel & Power Ltd.	0.0515	7.984	2649.56***	221***
Karnataka Bank Ltd.	0.6627	8.337	2545.63***	151.06***

(continued)



Table 1. Continued

Company	Skewness	Kurtosis	JB	ARCH test
Kesoram Industries Ltd.	0.2679	5.294	761.97***	404.26***
LIC Housing Finance Ltd.	0.4426	8.973	5039.97***	338.47***
Larsen & Toubro Ltd.	0.1392	5.881	1150.57***	296.06***
Lupin Ltd.	0.7182	7.149	2625.44***	301.86***
Mahanagar Telephone Nigam Ltd.	0.0249	5.770	1062.41***	315.22***
Maharashtra Seamless Ltd.	0.1193	8.859	4634.01***	209.5***
Matrix Laboratories Ltd.	0.1716	11.719	8552.7***	300.77***
Mphasis Ltd.	0.4501	7.539	2914.91***	252.64***
Nagarjuna Construction Company Ltd.	0.0905	6.177	1198.25***	246.32***
Nagarjuna Fertilizers & Chemicals Ltd.	0.2070	9.509	5881.17***	454.44***
National Aluminium Company Ltd.	0.0862	7.579	2873.54***	283.11***
Neyveli Lignite Corporation Ltd.	0.3680	10.423	6618.55***	261.44***
Patel Engineering Ltd.	0.1366	5.911	756.73***	258.35***
Rajesh Exports Ltd.	0.1289	5.781	696.71***	357.59***
Ranbaxy Laboratories Ltd.	-0.1273	8.278	3862.98***	367.78***
Reliance Capital Ltd.	0.0167	6.340	1543.73***	331.57***
Reliance Industries Ltd.	-0.3999	11.330	9692.2***	132.73***
Reliance Mediaworks Ltd.	0.0837	6.686	1326.62***	268.74***
Rolta India Ltd.	0.1954	6.812	2032.98***	265.75***
S Kumars Nationwide Ltd.	0.3598	7.172	2049.57***	232.09***
Satyam Computer Services Ltd.	-9.3228	286.764	11193691.62***	77.38
Shree Cement Ltd.	0.2588	5.446	802.17***	362.39***
Siemens Ltd.	0.0603	5.867	1139.2***	276.87***
State Bank of India Ltd.	-0.0154	5.895	1160.16***	354.39***
Steel Authority of India Ltd.	0.5579	8.905	4995.85***	351.56***
Sterlite Technology Ltd.	-0.0555	10.864	6162.5***	468.92***
Sun Pharmaceuticals Ltd.	0.1841	5.422	823.25***	651.31***
Syndicate Bank Ltd.	0.0535	9.723	4891.93***	304.9***
TVS Motor Company Ltd.	0.3478	7.704	3048.26***	261.89***
Tata Chemicals Ltd.	-0.0413	6.143	1367.74***	396.48***
Tata Motors Ltd.	-0.0541	5.232	690.53***	492.89***
Tata Power Company Ltd.	-0.0381	8.059	3543.44***	579.8***
Tata Steel Ltd.	-0.1958	5.602	958.1***	557.2***
Tata Tea Ltd.	0.1990	5.727	1050.95***	294.67***
Tata Teleservices (Maharashtra) Ltd.	0.7121	9.669	4629.68***	246.01***
Titan Industries Ltd.	0.4150	5.886	1243.32***	151.16***
Vijaya Bank Ltd.	0.2050	8.901	3406.7***	186.34***
Voltas Ltd.	0.3897	5.076	679.7***	226.73***
Wipro Ltd.	0.0347	6.793	1963.3***	493.79***
Wockhardt Ltd.	0.1638	6.325	1532.7***	314.56***
Zee Entertainment Enterprises Ltd.	-0.2322	6.543	1754***	297.21***

Notes: The Kurtosis reported in the table is in excess of three.

The JB test statistic is calculated as:  $JB = \frac{T}{6} \left( \hat{s}^2 + \frac{(\hat{k} - 3)^2}{4} \right) \sim \chi^2(2)$ , where,  $T$  is the total number of observations,  $\hat{s}$  the sample skewness and  $\hat{k}$  the sample kurtosis. LM is the Lagrange Multiplier test for ARCH effects (Engle, 1982), up to a lag of 12. The test statistic is again distributed as  $\chi^2(12)$ .

Only the  $p$ -values are reported.

\*\*\* Indicates test statistic significance at 1% level.

case of about 25 companies' stocks, no significant change in pattern of volatility is witnessed between the two regimes.

In summary, in most cases (76 out of 101), there seems to be a change in the structure of conditional volatility in the pre- and post-derivative regime. Subsequently, in order to analyse the structure of conditional volatility, three alternative switching asymmetric GARCH (1, 1) specifications are

evaluated. These models make the stock return volatility conditional on 'old' and 'new' information, allowing for asymmetric response to 'good' and 'bad' news, for the two regimes. Figure 4 reports the NIC for the three models stated above for each stock analysed. A flow chart of the process followed to arrive at the correct SAGARCH (1, 1) specification is given in Fig. 2. Also, an illustrative case has been discussed at the beginning of Fig. 4.

**Table 2. Wavelet variance analysis to detect volatility shifts at different time scales**

Company	Scale	$D_{Pre}$	$D_{Post}$
ABB	d8		
	d7		0.559
	d6	0.551	0.68***
	d5	0.249	0.184
	d4	0.335**	0.136
	d3	0.146	0.214***
	d2	0.225***	0.216***
	d1	0.171***	0.17***
ACC	d8		0.923
	d7	0.999**	0.459
	d6	0.375	0.312*
	d5	0.145	0.213*
	d4	0.175	0.189**
	d3	0.183**	0.194***
	d2	0.096	0.135***
	d1	0.155***	0.086***
Aban Offshore	d8	0.455	
	d7	0.299	
	d6	0.224	0.588
	d5	0.225*	0.403**
	d4	0.15*	0.312**
	d3	0.077	0.261***
	d2	0.104***	0.284***
	d1	0.173***	0.167***
Aditya Birla Nuvo	d8	0.563	
	d7	0.176	
	d6	0.474***	0.335
	d5	0.28***	0.239
	d4	0.23***	0.275*
	d3	0.467***	0.17
	d2	0.28***	0.175***
	d1	0.239***	0.149***
Alok Ind	d8		
	d7	0.558	0.367
	d6	0.435**	0.404
	d5	0.277**	0.349**
	d4	0.202**	0.261**
	d3	0.222***	0.222***
	d2	0.302***	0.16***
	d1	0.208***	0.252***
Alston Projects	d8		
	d7	0.308	
	d6	0.231	0.345
	d5	0.254*	0.237
	d4	0.12	0.257
	d3	0.182***	0.242**
	d2	0.148***	0.185***
	d1	0.128***	0.197***
Ambuja Cements	d8		0.962
	d7	0.992	0.339
	d6	0.336	0.378**
	d5	0.148	0.193
	d4	0.174	0.278***
	d3	0.145	0.191***
	d2	0.108*	0.103***
	d1	0.163***	0.191***

(continued)

**Table 2. Continued**

Company	Scale	$D_{Pre}$	$D_{Post}$
Arvind	d8		
	d7		0.746**
	d6	0.592	0.4*
	d5	0.185	0.329***
	d4	0.074	0.345***
	d3	0.104	0.215***
	d2	0.103	0.143***
	d1	0.087*	0.243***
Aurobindo Pharma	d8		
	d7		0.559
	d6	0.636**	0.375
	d5	0.304	0.333**
	d4	0.341***	0.277***
	d3	0.256***	0.32***
	d2	0.371***	0.326***
	d1	0.207***	0.182***
BEML	d8	0.31	
	d7	0.348	
	d6	0.154**	0.314
	d5	0.18	0.282
	d4	0.15	0.265*
	d3	0.096**	0.161
	d2	0.142***	0.156**
	d1	0.131***	0.113**
Ballarpur Industries	d8	0.314	
	d7	0.705**	
	d6	0.387	0.967
	d5	0.311***	0.38
	d4	0.338***	0.239
	d3	0.308***	0.23*
	d2	0.291***	0.222***
	d1	0.218**	0.112*
Balrampur Chini Mills	d8	0.482	
	d7	0.31	
	d6	0.221	0.371
	d5	0.127	0.239
	d4	0.112	0.147
	d3	0.15***	0.198**
	d2	0.073*	0.155**
	d1	0.048	0.172***
Bank of Baroda	d8	0.00	
	d7	0.312	0.396
	d6	0.303	0.278
	d5	0.229	0.181
	d4	0.138	0.129
	d3	0.18***	0.204***
	d2	0.113**	0.158***
	d1	0.074**	0.124***
Bank of India	d8	0.00	
	d7	0.568	0.318
	d6	0.403*	0.286
	d5	0.135	0.119
	d4	0.224**	0.117
	d3	0.146**	0.099
	d2	0.053	0.086*
	d1	0.1***	0.074**

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
Bharat Forge	d8	0.87	
	d7	0.506*	0.52
	d6	0.316	0.563**
	d5	0.249**	0.294*
	d4	0.199**	0.08
	d3	0.155***	0.227***
	d2	0.161***	0.279***
	d1	0.196***	0.219***
BHEL	d8		0.908
	d7	0.977	0.257
	d6	0.558**	0.32
	d5	0.191	0.122
	d4	0.183	0.255***
	d3	0.177**	0.179***
	d2	0.141***	0.09**
	d1	0.155***	0.086***
BPCL	d8		0.793
	d7	0.994*	0.177
	d6	0.241	0.233
	d5	0.348**	0.13
	d4	0.25**	0.12
	d3	0.274***	0.173***
	d2	0.237***	0.121***
	d1	0.201***	0.091***
Bharti Airtel	d8		
	d7		0.471
	d6		0.452
	d5	0.168	0.184
	d4	0.123	0.192
	d3	0.117	0.179***
	d2	0.119	0.221***
	d1	0.108**	0.186***
Bata	d8	0.43	
	d7	0.428	
	d6	0.232	0.232
	d5	0.165	0.162
	d4	0.153*	0.124
	d3	0.105*	0.18*
	d2	0.094***	0.115
	d1	0.08***	0.168***
Bombay Dyeing	d8	0.375	
	d7	0.4	
	d6	0.224	0.254
	d5	0.238**	0.326
	d4	0.143*	0.135
	d3	0.111**	0.156
	d2	0.069	0.205***
	d1	0.088***	0.122***
CESC	d8		
	d7	0.35	0.481
	d6	0.33	0.424
	d5	0.208	0.231
	d4	0.101	0.167
	d3	0.088	0.247***
	d2	0.083*	0.157***
	d1	0.055*	0.096***

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
Century Textiles	d8	0.764	
	d7	0.511*	0.899
	d6	0.137	0.376
	d5	0.24*	0.241
	d4	0.233***	0.174
	d3	0.185***	0.205***
	d2	0.095**	0.174***
	d1	0.081***	0.116***
Chambal Fertilizers	d8	0.99	
	d7	0.311	0.5
	d6	0.294	0.482*
	d5	0.12	0.305*
	d4	0.269***	0.298***
	d3	0.146***	0.389***
	d2	0.126***	0.294***
	d1	0.158***	0.316***
Chennai Petroleum	d8	0.903	
	d7	0.253	0.382
	d6	0.287	0.46*
	d5	0.113	0.263
	d4	0.122	0.175
	d3	0.196***	0.212***
	d2	0.086**	0.122**
	d1	0.115***	0.121***
Cipla	d8		0.731
	d7	0.811	0.46
	d6	0.325	0.183
	d5	0.374**	0.168
	d4	0.156**	0.141
	d3	0.179**	0.079
	d2	0.213***	0.08*
	d1	0.14***	0.093***
Colgate Palmolive	d8	0.97***	
	d7	0.34	
	d6	0.331**	0.965**
	d5	0.199*	0.381
	d4	0.272***	0.236
	d3	0.178***	0.185
	d2	0.206***	0.247***
	d1	0.196***	0.153***
Corporation Bank	d8		
	d7	0.628**	0.47
	d6	0.246	0.342
	d5	0.41***	0.204
	d4	0.22***	0.117
	d3	0.181***	0.177**
	d2	0.175***	0.083
	d1	0.074**	0.096***
Crompton Greaves	d8	0.721	
	d7	0.615***	
	d6	0.257	0.652**
	d5	0.355***	0.313
	d4	0.279***	0.14
	d3	0.209***	0.201**
	d2	0.157***	0.153**
	d1	0.125***	0.145***

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
Cummins India	d8		
	d7	0.418	0.93*
	d6	0.287	0.536**
	d5	0.176	0.165
	d4	0.15	0.229**
	d3	0.142***	0.166**
	d2	0.148***	0.084*
	d1	0.115***	0.082**
Dabur India	d8	0.804	
	d7	0.475	0.981**
	d6	0.33*	0.302
	d5	0.231*	0.213
	d4	0.241***	0.192
	d3	0.257***	0.166**
	d2	0.202***	0.132***
	d1	0.156***	0.136***
Dena Bank	d8	0.525	
	d7	0.443*	
	d6	0.273	0.284
	d5	0.241**	0.203
	d4	0.162**	0.108
	d3	0.103*	0.183*
	d2	0.133***	0.24***
	d1	0.099***	0.105**
Escorts	d8	0.923	
	d7	0.446	0.485
	d6	0.286	0.341
	d5	0.205	0.156
	d4	0.264***	0.166
	d3	0.223***	0.074
	d2	0.103***	0.108*
	d1	0.081***	0.117***
Federal Bank	d8	0.574	0.00
	d7	0.232	0.788
	d6	0.131	0.383
	d5	0.193	0.249
	d4	0.154*	0.127
	d3	0.119*	0.136
	d2	0.098**	0.112**
	d1	0.067**	0.095***
GTL	d8	0.47	
	d7	0.488*	
	d6	0.386**	0.323
	d5	0.327***	0.343
	d4	0.27***	0.35***
	d3	0.266***	0.35***
	d2	0.196***	0.324***
	d1	0.17***	0.274***
Glaxosmithkline	d8	0.904	
	d7	0.432	0.5
	d6	0.36**	0.216
	d5	0.221*	0.284
	d4	0.136	0.179
	d3	0.241***	0.144*
	d2	0.188***	0.195***
	d1	0.199***	0.147***

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
Grasim Industries	d8		
	d7	0.418	0.535
	d6	0.287**	0.389
	d5	0.176*	0.2
	d4	0.15	0.117
	d3	0.142***	0.092
	d2	0.148***	0.088
	d1	0.115***	0.109
Great Eastern Shipping Company	d8	0.897	
	d7	0.246	
	d6	0.145	0.183
	d5	0.133	170.193
	d4	0.116***	0.207
	d3	0.114**	0.212*
	d2	0.105***	0.174***
	d1	0.127***	0.159***
Gujarat Narmada Valley Fertilizers Co	d8	0.989	
	d7	0.579**	0.498
	d6	0.182	0.386
	d5	0.317***	0.305*
	d4	0.267***	0.199*
	d3	0.208***	0.163**
	d2	0.122***	0.152***
	d1	0.11***	0.118***
HDFC Bank	d8		0.913
	d7	0.617	0.303
	d6	0.226	0.554***
	d5	0.2	0.222*
	d4	0.31***	0.211***
	d3	0.195**	0.33***
	d2	0.169***	0.271***
	d1	0.126***	0.184***
Hero Honda	d8		
	d7	0.59	0.535
	d6	0.401*	0.389**
	d5	0.198	0.2
	d4	0.143	0.117
	d3	0.19***	0.092
	d2	0.076	0.088*
	d1	0.048	0.109***
Hindalco Industries	d8		0.579
	d7	0.972	0.214
	d6	0.201	0.358**
	d5	0.19	0.284***
	d4	0.165	0.36***
	d3	0.163*	0.31***
	d2	0.119**	0.308***
	d1	0.177***	0.272***
Hindustan Construction Company	d8	0.492	
	d7	0.265	
	d6	0.391**	0.39
	d5	0.234**	0.266
	d4	0.16	0.16

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
Hindustan Petroleum Corporation	d3	0.19**	0.19**
	d2	0.2***	0.2***
	d1	0.144***	0.144***
	d8	1**	1**
	d7	0.259	0.259
	d6	0.231	0.231
	d5	0.194	0.194
	d4	0.132	0.132
Hindustan Unilever	d3	0.135**	0.135**
	d2	0.142***	0.142***
	d1	0.1***	0.1***
	d8	0.999**	0.999**
	d7	0.317	0.317
	d6	0.138	0.138
	d5	0.135	0.135
	d4	0.099	0.099
Hotel Leelaventures	d3	0.12**	0.12**
	d2	0.063	0.063
	d1	0.097***	0.097***
	d8		
	d7		
	d6	0.375	0.515
	d5	0.342*	0.216
	d4	0.169	0.085
HDFC	d3	0.202*	0.247***
	d2	0.114***	0.142**
	d1	0.098***	0.156***
	d8		0.913
	d7	0.617	0.303
	d6	0.226	0.554***
	d5	0.2	0.222*
	d4	0.31***	0.211***
ICICI Bank	d3	0.195**	0.33***
	d2	0.169***	0.271***
	d1	0.126***	0.184***
	d8		0.408
	d7	0.603	0.408
	d6	0.31	0.568***
	d5	0.187	0.276**
	d4	0.159	0.412***
IFCI	d3	0.224	0.335***
	d2	0.118**	0.261***
	d1	0.117**	0.288***
	d8	0.967	
	d7	0.477	0.499
	d6	0.449***	0.477*
	d5	0.281**	0.203
	d4	0.268***	0.176
ITC	d3	0.209***	0.134
	d2	0.277***	0.112**
	d1	0.193***	0.123***
	d8		0.957
	d7	0.847	0.347
	d6	0.505*	0.235
	d5	0.23	0.126

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
IVRCL	d4	0.359***	0.097
	d3	0.129	0.225***
	d2	0.132**	0.143***
	d1	0.103***	0.065**
	d8		0.631
	d7	0.487	0.523**
	d6	0.267	0.16
	d5	0.345**	0.399***
India Cements	d4	0.317***	0.22***
	d3	0.193***	0.29***
	d2	0.229***	0.213***
	d1	0.186***	
	d8		0.572
	d7	0.406	0.319
	d6	0.127	0.223
	d5	0.266**	0.106
Indian Hotels Co	d4	0.231***	0.097
	d3	0.165***	0.162***
	d2	0.13***	0.093***
	d1	0.096***	
	d8	0.9	0.698
	d7	0.305	0.592
	d6	0.17	0.235***
	d5	0.103	0.149
Indian Overseas Bank	d4	0.18**	0.249***
	d3	0.248***	0.099*
	d2	0.107***	0.144***
	d1	0.091***	
	d8		0.472
	d7	0.673	0.603***
	d6	0.566**	0.253
	d5	0.196	0.176
Indusind Bank	d4	0.352***	0.199***
	d3	0.344***	0.099*
	d2	0.29***	0.12***
	d1	0.166***	
	d8		0.408
	d7	0.206	0.161
	d6	0.223	0.241
	d5	0.385***	0.088
Infosys Technologies	d4	0.161	0.187**
	d3	0.217***	0.088
	d2	0.078	0.111***
	d1	0.155***	
	d8		0.624
	d7	0.961	0.564**
	d6	0.254	0.207
	d5	0.357**	0.256**
JSW Steel	d4	0.179	0.3***
	d3	0.297***	0.263***
	d2	0.129**	0.114***
	d1	0.206***	0.203***
	d8	0.511	
	d7	0.261	0.218
	d6	0.256	0.173
	d5	0.154	

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
Jammu & Kashmir Bank	d4	0.132	0.29**
	d3	0.171***	0.171*
	d2	0.183***	0.186***
	d1	0.173***	0.144***
	d8		
	d7	0.574	0.83
	d6	0.255	0.542**
	d5	0.298**	0.437***
Jindal Steel	d4	0.098	0.153
	d3	0.168***	0.151*
	d2	0.126***	0.109*
	d1	0.18***	0.068
	d8		
	d7	0.559	0.846
	d6	0.68***	0.417
	d5	0.184	0.24
Karnataka Bank	d4	0.136	0.219**
	d3	0.214***	0.282***
	d2	0.216***	0.263***
	d1	0.17***	0.225***
	d8		
	d7		0.739
	d6	0.4	0.454*
	d5	0.163	0.288
Kesoram Industries	d4	0.256*	0.114
	d3	0.168	0.098
	d2	0.149**	0.135***
	d1	0.194***	0.082**
	d8	0.84	
	d7	0.454*	
	d6	0.433***	0.281
	d5	0.318***	0.323
LIC Housing Finance	d4	0.28***	0.145
	d3	0.196***	0.164
	d2	0.166***	0.156**
	d1	0.169***	0.13***
	d8	0.55	
	d7	0.277	0.541
	d6	0.346*	0.46*
	d5	0.232*	0.214
Larson & Toubro	d4	0.261***	0.22**
	d3	0.201***	0.359***
	d2	0.118***	0.314***
	d1	0.117***	0.254***
	d8	0.935*	
	d7	0.547**	
	d6	0.311*	0.35
	d5	0.285***	0.194
Lupin	d4	0.271***	0.147
	d3	0.205***	0.203**
	d2	0.171***	0.207***
	d1	0.18***	0.157
	d8	0.5	
	d7	0.249	
	d6	0.214	0.335
	d5	0.234**	0.125

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
MTNL	d4	0.298***	0.129
	d3	0.272***	0.125
	d2	0.232***	0.113
	d1	0.192***	0.131***
	d8		0.538
	d7	0.781	0.362
	d6	0.415	0.36**
	d5	0.119	0.152
Mahindra & Mahindra	d4	0.316***	0.166*
	d3	0.178**	0.102
	d2	0.165***	0.1***
	d1	0.144***	0.075***
	d8		0.784
	d7	0.789	0.314
	d6	0.238	0.388**
	d5	0.147	0.084
Matrix Laboratories	d4	0.144	0.139
	d3	0.242***	0.338***
	d2	0.215***	0.186***
	d1	0.188***	0.109***
	d8		
	d7	0.523	0.611
	d6	0.336	0.223
	d5	0.322**	0.343*
Mphasis	d4	0.326***	0.425***
	d3	0.337***	0.384***
	d2	0.381***	0.204***
	d1	0.43***	0.208***
	d8		
	d7	0.226	0.807
	d6	0.38**	0.384
	d5	0.323***	0.217
Nagarjuna Construction	d4	0.266***	0.156
	d3	0.31***	0.149*
	d2	0.251***	0.16***
	d1	0.236***	0.127***
	d8		
	d7	0.145	
	d6	0.39**	0.362
	d5	0.258**	0.355
Nagarjuna Fertilizers	d4	0.266***	0.22
	d3	0.258***	0.219**
	d2	0.254***	0.198***
	d1	0.221***	0.144***
	d8	0.648	
	d7	0.32	0.441
	d6	0.443	0.225
	d5	0.187***	0.227
National Aluminium Company	d4	0.243	0.171
	d3	0.295***	0.169**
	d2	0.191***	0.189***
	d1	0.16***	0.193***
	d8		
	d7	0.4	0.484
	d6	0.344	0.447**

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
	d5	0.295**	0.239*
	d4	0.258***	0.288***
	d3	0.153**	0.262***
	d2	0.114**	0.209***
	d1	0.095***	0.167***
Neyveli Lignite	d8		
	d7	0.244	0.935**
	d6	0.328	0.477**
	d5	0.316**	0.278
	d4	0.168	0.181
	d3	0.333***	0.223***
	d2	0.251***	0.188***
	d1	0.33***	0.239***
Patel Engineering	d8		
	d7	0.303	
	d6	0.215	0.338
	d5	0.122	0.207
	d4	0.213**	0.251
	d3	0.2***	0.264***
	d2	0.204***	0.224***
	d1	0.227***	0.173***
Rajesh Exports	d8		
	d7	0.51	
	d6	0.214	0.5
	d5	0.293*	0.219
	d4	0.417***	0.227
	d3	0.43***	0.215**
	d2	0.238***	0.181***
	d1	0.241***	0.142***
Ranbaxy Laboratories	d8		0.982
	d7	0.884	0.384
	d6	0.343	0.403**
	d5	0.23	0.25**
	d4	0.228*	0.392***
	d3	0.237***	0.256***
	d2	0.292***	0.275***
	d1	0.31***	0.279***
Reliance Capital	d8	0.961	
	d7	0.536*	0.875
	d6	0.205	0.576**
	d5	0.33***	0.278
	d4	0.28***	0.152
	d3	0.183***	0.255***
	d2	0.187***	0.187***
	d1	0.126***	0.16***
Reliance Industries	d8		0.989
	d7	1**	0.428
	d6	0.323	0.425***
	d5	0.199	0.143
	d4	0.263**	0.199**
	d3	0.146	0.334***
	d2	0.106*	0.196***
	d1	0.082*	0.145***
Reliance Media works	d8		
	d7	0.261	
	d6	0.301	0.25

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
	d5	0.163	0.269
	d4	0.148	0.134
	d3	0.138*	0.261***
	d2	0.142***	0.198***
	d1	0.104***	0.2***
Rolta India	d8	0.405	
	d7	0.667***	
	d6	0.261	0.756**
	d5	0.312***	0.391*
	d4	0.198***	0.211
	d3	0.25***	0.228**
	d2	0.225***	0.204***
	d1	0.17***	0.153***
S Kumars	d8		
	d7	0.649**	
	d6	0.256	0.497
	d5	0.2	0.284
	d4	0.135	0.264
	d3	0.171***	0.198***
	d2	0.154***	0.143***
	d1	0.196***	0.168***
Satyam Computer Services	d8		0.606
	d7	0.952	0.314
	d6	0.342	0.498***
	d5	0.177	0.651***
	d4	0.145	0.739***
	d3	0.19**	0.503***
	d2	0.146***	0.637***
	d1	0.163***	0.366***
Shree Cements	d8	0.576	
	d7	0.678***	
	d6	0.222	0.473
	d5	0.41***	0.203
	d4	0.276***	0.204
	d3	0.345***	0.183*
	d2	0.267***	0.125
	d1	0.279***	0.121***
Siemens	d8	0.66	
	d7	0.367	0.798
	d6	0.429***	0.571**
	d5	0.214**	0.331**
	d4	0.365***	0.186
	d3	0.267***	0.127
	d2	0.306***	0.215***
	d1	0.204***	0.132***
State Bank of India	d8		0.821
	d7	0.554	0.186
	d6	0.315	0.529***
	d5	0.25	0.141
	d4	0.258**	0.287***
	d3	0.115	0.277***
	d2	0.16***	0.178***
	d1	0.093**	0.145***
Steel Authority of India	d8	0.625	
	d7	0.388	
	d6	0.23	0.465

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
	d5	0.153	0.17
	d4	0.297***	0.123
	d3	0.216***	0.185**
	d2	0.136***	0.161***
	d1	0.168***	0.134***
Sterlite Technology	d8		
	d7	0.337	
	d6	0.133	0.332
	d5	0.323**	0.258
	d4	0.266***	0.231
	d3	0.147**	0.209**
	d2	0.176***	0.228***
	d1	0.112***	0.22***
Sun Pharmaceuticals	d8		
	d7	0.344	0.622
	d6	0.459***	0.337
	d5	0.388***	0.311*
	d4	0.393***	0.183
	d3	0.366***	0.253***
	d2	0.264***	0.112**
	d1	0.198***	0.158***
Syndicate Bank	d8		
	d7		0.289
	d6	0.65**	0.269
	d5	0.426**	0.134
	d4	0.414***	0.147
	d3	0.16	0.147**
	d2	0.306***	0.123***
	d1	0.14***	0.094***
TVS Motors	d8		
	d7	0.23	0.488
	d6	0.22	0.314
	d5	0.125	0.356*
	d4	0.186**	0.15
	d3	0.138**	0.168**
	d2	0.113***	0.187***
	d1	0.133***	0.193***
Tata Chemicals	d8	0.97	
	d7	0.436	0.509
	d6	0.25	0.617***
	d5	0.153	0.41***
	d4	0.105	0.244**
	d3	0.098	0.357***
	d2	0.088**	0.261***
	d1	0.132***	0.21***
Tata Motors	d8		0.585
	d7	0.561	0.383
	d6	0.37	0.717***
	d5	0.174	0.103
	d4	0.218*	0.253***
	d3	0.163*	0.296***
	d2	0.162***	0.299***
	d1	0.158***	0.16***
Tata Power	d8		0.994*
	d7	0.923	0.502*
	d6	0.305	0.425***

(continued)

Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
	d5	0.234	0.203
	d4	0.356***	0.304***
	d3	0.197**	0.258***
	d2	0.254***	0.196***
	d1	0.197***	0.189***
Tata Steel	d8		0.998*
	d7	0.602	0.251
	d6	0.199	0.613***
	d5	0.11	0.147
	d4	0.182	0.327***
	d3	0.129	0.351***
	d2	0.144***	0.216***
	d1	0.146***	0.231***
Tata Tea	d8		0.992
	d7	0.642	0.287
	d6	0.32	0.235
	d5	0.204	0.099
	d4	0.156	0.156*
	d3	0.085	0.085
	d2	0.187***	0.094**
	d1	0.105***	0.062**
Tata Teleservices	d8		
	d7	0.339	
	d6	0.265	0.323
	d5	0.26*	0.212
	d4	0.119	0.168
	d3	0.153***	0.213**
	d2	0.168***	0.194***
	d1	0.133***	0.174***
Titan Industries	d8	0.839	
	d7	0.334	0.434
	d6	0.273	0.198
	d5	0.113	0.2
	d4	0.218***	0.25**
	d3	0.079	0.127
	d2	0.078*	0.125**
	d1	0.077***	0.123***
Vijaya Bank	d8		
	d7	0.827	0.8
	d6	0.441	0.507**
	d5	0.269	0.33**
	d4	0.219*	0.197*
	d3	0.247***	0.21***
	d2	0.213***	0.106*
	d1	0.072	0.131***
Voltas	d8	0.758	
	d7	0.517**	
	d6	0.404***	0.399
	d5	0.282***	0.358
	d4	0.165***	0.134
	d3	0.226***	0.166
	d2	0.151***	0.16**
	d1	0.128***	0.147***
Wipro	d8		
	d7	0.487	0.3
	d6	0.317	0.465**

(continued)



Table 2. Continued

Company	Scale	$D_{Pre}$	$D_{Post}$
	d5	0.186	0.281**
	d4	0.175	0.146
	d3	0.145**	0.166***
	d2	0.147***	0.143***
	d1	0.184***	0.098***
Wockhardt	d8		
	d7	0.365	0.681
	d6	0.426**	0.564**
	d5	0.262**	0.362**
	d4	0.226***	0.247**
	d3	0.365***	0.203***
	d2	0.215***	0.182***
Zee Entertainment	d1	0.209***	0.257***
	d8	0.499	
	d7	0.318	
	d6	0.301	0.551
	d5	0.366*	0.249
	d4	0.297***	0.335**
	d3	0.269***	0.146
	d2	0.228***	0.225***
d1	0.181***	0.171***	

Note: \*\*\*, \*\* and \* indicate test statistic significance at 1, 5 and 10% levels, respectively.

Frequency at which there exists a structural break in volatility	Low	High	Low and high
Post derivatives			
Pre derivatives			
Low	11 companies	0	28 companies
High	0	0	
Low and high	48 companies	0	14 companies

Fig. 1. Summary of the wavelet variance analysis test results

Accordingly, in the case of most of the companies' stocks analysed (88 out of 101), a GJR GARCH model was found suitable. In most of these cases, the EGARCH specification was also appropriate, but the EGARCH model returned an unreasonably large conditional volatility for very 'bad' news (large negative values of  $\varepsilon_{t-1}$ ). Also, in such cases, the conditional volatility given by the EGARCH model remained more or less constant for 'good' news (positive values of  $\varepsilon_{t-1}$ ). Thus, in such cases, a GJR GARCH specification was preferred because it adequately captured response of volatility to both 'good' as well as 'bad' news. This finding is in conformity with Engle and Ng (1993) and Kim and Kon (1994), who find GJR GARCH to be a more appropriate specification among alternative asymmetric GARCH models. A PGARCH was found appropriate in the case of another 10 stocks and EGARCH in the case

of 3 stocks. Table 3 reports the results of the switching asymmetric GARCH specification of conditional volatility. An illustrative case is explained in the notes to Table 3. Relevant results from Table 3 are summarized in Fig. 3.

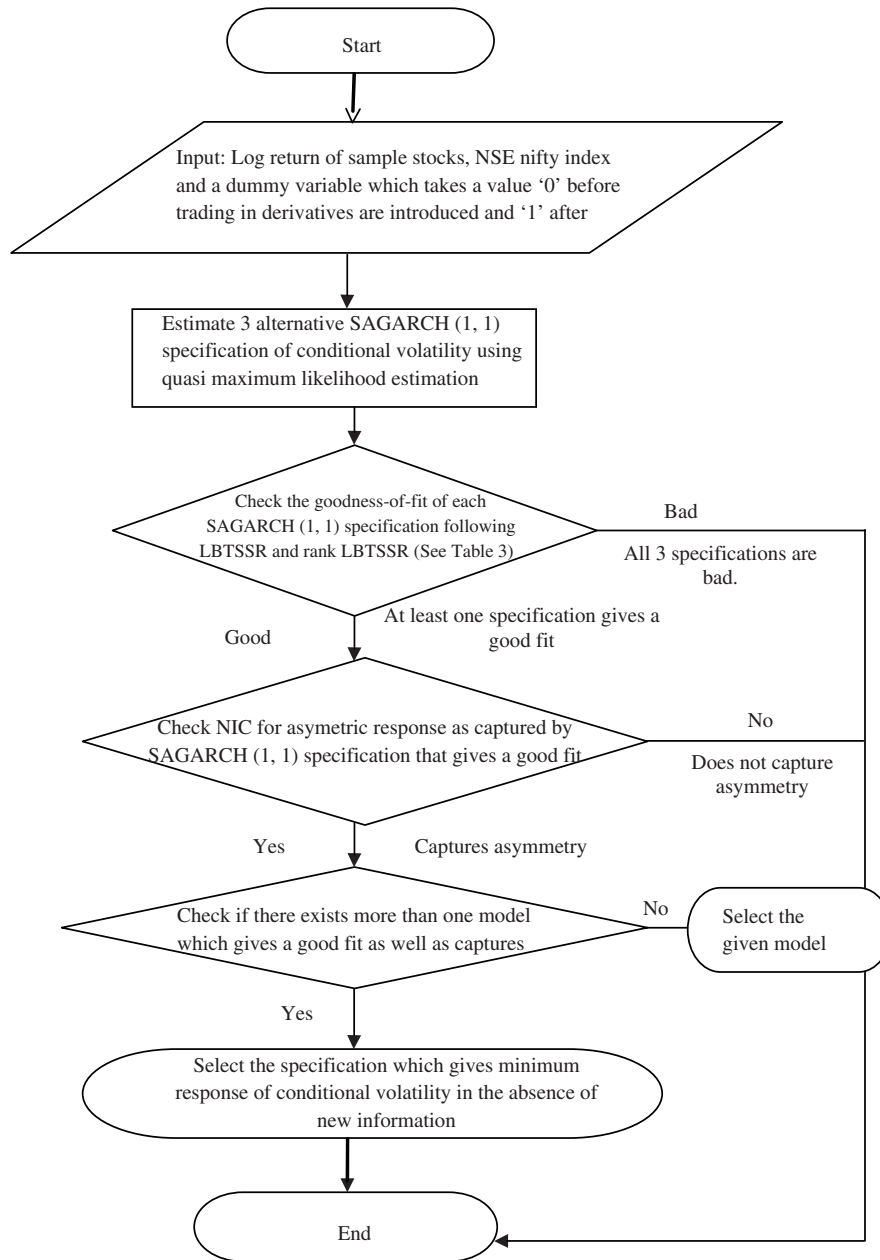
Based on Table 3 (summarized in Fig. 3), the following observations can be made:

- (i) In more than 85% of the cases, the SAGARCH (1, 1) model was found to be a good fit. In other words, post fit there was no evidence of autocorrelation in the squared residuals.
- (ii) The unconditional volatility for different switching asymmetric GARCH (1, 1) specifications has increased in 60 of the 101 stocks analysed. Thus, hinting at an increase in the quantity of information flowing into the spot markets after introduction of derivatives trading.
- (iii) In the case of 61 stocks, the asymmetric response is either reduced or removed completely after introduction of derivatives trading. In the case of another 22 stocks, the extent of asymmetry is more pronounced in the post-derivatives regime. In the case of 18 stocks, the introduction of derivatives trading does not seem to affect asymmetric response. Thus, if the asymmetric response was due to market imperfections, (reaction of noise traders as in Black (1986)), then in the case of more than 60% of the stocks analysed, the introduction of derivatives trading seems to have increased the information efficiency of the stock market.
- (iv) The 'news coefficient' decreased in the case of 73 stocks. In other words, the introduction of derivative trading seems to have reduced the rate of absorption of 'new' information into spot prices.
- (v) The 'persistence coefficient' has reduced in the case of all the stocks analysed. In other words, the impact of 'old' information on current volatility seems to have reduced.

### Discussion

Based on the results, it can be said that while the introduction of derivatives trading has mostly reduced (and not removed) asymmetric response of volatility, it has also reduced the impact of 'old' information on stock prices, as well as the speed with which 'new' information is incorporated in prices.

At the outset, this sounds counter intuitive because theoretically, the reduction in spot market return volatility happens because of lower dependence on past volatility and higher rate at which 'new' information is being reflected in stock prices. To explain



**Fig. 2.** Flow chart for the process followed to select the (switching SAGARCH (1, 1)) asymmetric GARCH (1, 1) model of conditional volatility

this counter intuitive finding, let me start with an analysis of past studies that examine the said issue (Antoniou and Holmes, 1995; Bologna and Cavallo, 2002; Bandivadekar and Ghosh, 2003). Their conclusion that introduction of derivatives leads to a reduction in persistence (effect of 'old' information) due to an increase in rate of absorption of 'new' information is based on the following premises:

- (i) Introduction of derivatives trading would lead the informed speculators as well as the noise traders to migrate to the derivative market,

thus creating a new set of active information seekers in this market.

- (ii) Consequently, there would be a lot of information that is being generated in the derivatives market and then transmitted to the spot market.
- (iii) Post migration of noise traders, the remaining investors would use this 'new' information to arrive at a fair price rapidly.

In reality, a lot depends on the quality of the information emanating from the derivatives market.

Table 3. Coefficient estimates for the switching asymmetric GARCH (1,1) specification of conditional volatility

Company	Asymmetric GARCH model	C	Asymmetric GARCH (1,1) specification of conditional volatility										Unconditional volatility			
			$\theta_1$	$\theta_2$	$\omega_0(\times 10^5)$	$\alpha_1$	$\alpha_2$	$\gamma_1(\times 10^5)$	$\beta_0(\times 10^2)$	$\beta_1(\times 10^2)$	$\beta_2(\times 10^2)$	$\gamma_2(\times 10^2)$	$\delta_1$	$\delta_2$	LBTSSR	Rank
ABB Ltd.	GJR	3.28	0.06***	0.272	1.49***	0.09***	0.81***	-1.03***	0.025	7.28***	7.83***	0.7	37.22***	30.78***	1E-04	-0.03
ACC Ltd.	GJR	4.11**	0.04***	0.32***	3.23***	0.07***	0.73***	-2.67***	0.69	11.98**	11.89***	-1.42	27.92**	18.57	2E-04	0.009
Aban Offshore Ltd.	GJR	4.38*	0.03*	0.15***	0.92***	0.07***	0.84***	-0.19	-3.5	1.81	10.84***	8.95**	37.88***	31.45***	1E-04	-0.04
Aditya Birla Nuvo Ltd.	GJR	5.56**	0.06***	0.19***	0.89***	0.03***	0.87***	-0.27	5***	-2.59	13.55***	1.23	22.94*	20.98	9E-05	0.057
Alok Industries Ltd.	GJR	6.59***	0.06***	0.14***	0.9***	0.09***	0.84***	-0.38*	-2.61	4.04*	8.16***	2.81	15.65	14.38	1E-04	-0.03
Alstom Projects India Ltd.	GJR	4.07*	0.07***	0.15***	1.43***	0.07***	0.78***	-0.85***	0.96	8.68***	15.08***	-3.78	17.63	13.02	9E-05	0.012
Ambuja Cements Ltd.	Exponential	3.29	0.06***	0.33***	-16014***	-0.92***	0.03	15665***	1.87***	0.21***	0.09	-6.64	21.87	20.11	0.987	1.02
Arvind Ltd.	GJR	6.26***	0.05***	0.21***	0.46***	0.06***	0.91***	-0.09	-0.74	-2.54	2.12	9.05***	27.71**	23.53*	2E-04	-0.01
Aurobindo Pharma Ltd.	GJR	3.14	0.06***	0.2***	0.7***	0.05	0.87***	-0.02	0.73	-1.62	10.63***	4.05	33.53***	26.79**	9E-05	0.008
BEML Ltd.	Power	5.07**	0.07***	0.16***	0.55	0.12***	0.82***	46.44	1.02	4.11**	-18.05***	-33***	46.44	18.62	5E-09	0.004
Ballarpur Industries Ltd.	GJR	6.45***	0.06***	0.2***	1.1***	0.06***	0.83***	-0.86***	-1.31	6.9***	11.61***	-0.3	32.17***	16.29	1E-04	-0.02
Balrampur Chini Mills Ltd.	GJR	4.25*	0.06***	0.17***	1.39***	0.06***	0.8***	-0.6**	2.17	7.18***	15.21***	-8.72**	27.56**	23.72*	1E-04	0.026
Bank of Baroda	GJR	4.57**	0.04***	0.25***	-14498***	0.83***	0.25***	118272***	14***	-2.87	-6.95***	2.0***	16.14	4.74	9E-04	-0.07
Bank of India	GJR	4.76**	0.02	0.25***	1.72***	0.05***	0.8***	-1.23***	1.21	7.45**	12.25***	-3.89	24.65**	17.79	1E-04	0.015
Bata India Ltd.	GJR	5.04**	0.07***	0.18***	0.96***	0.06***	0.84***	-0.47**	-0.92	5.02**	10.12***	-0.82	29.82**	20.38	2E-04	0.004
Bharat Forge Ltd.	Power	2.56	0.06***	0.22***	48.49***	0.09***	0.89***	-31.25	3.2**	-1.62	-31.36***	-5.02	1.02***	0.18	2E-04	0.004
Bharat Heavy Electricals Ltd.	GJR	2.61	0.05***	0.33***	1.91***	0.1***	0.8***	-1.33***	-4.26*	5.49**	4.2	6.09*	14.78	6.26	2E-04	-0.05
Bharat Petroleum Corporation Ltd.	GJR	5.99***	0.07***	0.18***	2.44***	0.05***	0.82***	-1.77***	0.17	2.83	9.67***	5.43	21.57	17.97	2E-04	0.002
Bharti Airtel Ltd.	GJR	5.45**	0.07***	0.25***	2.2***	0.02	0.73***	-1.85***	5.02	13.63***	18.76***	-7.52	13.4	7.73	9E-05	0.07
Birla Corporation Ltd.	GJR	5.11**	0.05**	0.14***	0.89***	0.07***	0.83***	-0.44**	-1.15	5.8**	11.62***	-2.07	16.82	10.5	9E-05	-0.01
Power	Power	4.49**	0.05	0.2***	-4.13***	0.06***	0.96***	614.72	2.05	-4.74***	-23.42***	-40***	43.73***	17.38	4E-04	3E-06

(continued)



HDFC Bank Ltd.	GJR	1.93	0.04***	0.34***	0.8***	0.03**	0.9***	-0.16	2.4	-4.92**	6.54***	7.22***	29.27**	18.8	1E-04	0.025
Hero Honda Motors Ltd.	GJR	4.71**	0.08***	0.23***	1.47***	0.05***	0.84***	-0.64**	0.96	-0.77	11.22***	6.56*	23.54*	20.79	1E-04	0.011
Hindalco Industries Ltd.	GJR	5.28***	0.04**	0.32***	2.1***	0.04***	0.82***	-1.48***	1.73	2.43	12.75***	0.28	22.41*	17.96	1E-04	0.02
Hindustan Construction Company Ltd.	GJR	4.68**	0.06***	0.15***	0.96***	0.09***	0.83***	-0.43*	-1.78	2.86	9.79***	4.47	20.4	15.6	1E-04	-0.02
Hindustan Petroleum Corporation Ltd.	GJR	6.24***	0.07***	0.2***	2.3***	0.04***	0.82***	-1.57***	2.02	0.43	10.24***	6.25*	35.86***	22.97*	2E-04	0.023
Hindustan Unilever Ltd.	GJR	5.35**	0.06***	0.37***	2.67***	0.04***	0.78***	-2.28***	3.12	9.73**	10.8***	-5.83*	27.02**	18.06	2E-04	0.038
Hotel Leelaventure Ltd.	GJR	4.07*	0.06***	0.18***	0.98***	0.04***	0.86***	-0.55***	4.42***	2.57	11.06***	-4.98*	26.51**	20.65	1E-04	0.05
Housing Development Finance Corporation Ltd.	Exponential	1.09	0.07***	0.30***	-8.815***	0.89***	0.17***	0.26	3.64	9.98***	-9.71***	-3.61	21.55	18.11	0.14	1.141
ICICI Bank Ltd.	Exponential	3.99*	-0.06	0.33***	7.63***	0.91***	0.20***	-1.379***	-1.57	4.14	-6.78***	1.97	23.46*	8.50	0.208	0.206
IFCI Ltd.	GJR	5.53**	0.07***	0.15***	1.48***	0.07***	0.81***	-0.91***	0.93	4.97**	12.26***	-2.38	25.46**	24.67	1E-04	0.011
ITC Ltd.	GJR	4.3**	0.08***	0.35***	3.09***	0.05**	0.72***	-2.51***	1.39	13.51***	16.19***	-5.71	13.9	12.7*	1E-04	0.019
IVRCL Infrastructures & Projects Ltd.	Power	2.14	0.04*	0.16***	40.83***	0.1***	0.89***	-27.51	3.2*	-4.5**	-35.95***	-8.82	29.6**	11.41	3E-04	4E-05
India Cements Ltd.	GJR	5.95***	0.05***	0.21***	0.8***	0.07***	0.86***	-0.51***	0.86	3.12	7.36***	-2.27	32.8***	13.68	1E-04	0.01
Indian Hotels Company Ltd.	GJR	4.31*	0.04**	0.3***	1.02***	0.06**	0.85***	-0.72**	0.63	4.71**	9.78***	-3.64	22.32*	16.45	1E-04	0.007
Indian Overseas Bank	GJR	4.04*	0.03	0.2***	1.98***	0.05*	0.71***	-1.48***	1.18	15.12***	21.91***	-9.28**	18.98	11.37	8E-05	0.017
Indusind Bank Ltd.	GJR	5.01**	0.05***	0.19***	1.12***	0.05***	0.82***	-0.72***	3.12*	5.93**	15.72***	-9.61***	27.35**	21.08	9E-05	0.037
Infosys Technologies Ltd.	GJR	1.16	0.11***	0.3***	1.45***	0.06***	0.83***	-1.06**	1.71	3.09	9.22***	0.82	24.41*	20.66	1E-04	0.02
JSW Steel Ltd.	Power	2.36	0.07***	0.15***	99.43***	0.13***	0.85***	324.46	-1.13	2.28	-43.38***	-20.27	0.91***	19.25	6E-04	2E-04
Jammu & Kashmir Bank Ltd.	GJR	4.62*	0.06***	0.17***	1***	0.07***	0.82***	-0.51**	-0.67	4.49*	13.29***	0.2	26.02**	18.86	9E-05	-0.01
Jindal Steel & Power Ltd.	GJR	1.36	0.05***	0.23***	1.21***	0.06**	0.79***	-0.67**	0.83	7.43**	15.56***	-4.96	15.98	10.55	8E-05	0.01
Karnataka Bank Ltd.	GJR	7.84***	0.05**	0.18***	1.79***	0.05	0.75***	-1.29**	2.47	10.26**	14.97***	-0.67	27.41**	14.54	9E-05	0.033
Kesoram Industries Ltd.	GJR	4.87**	0.05***	0.19***	0.85***	0.06***	0.85***	-0.3	-0.29	2.05	8.55***	4.18	19.46	21.65	1E-04	-0

(continued)

Table 3. Continued

Company	Asymmetric GARCH model	C ( $\times 10^4$ )	$\theta_1$	$\theta_2$	$\alpha_0(\times 10^5)$	$\alpha_1$	$\alpha_2$	$\gamma_1(\times 10^5)$	$\beta_0(\times 10^2)$	$\beta_1(\times 10^2)$	$\beta_2(\times 10^2)$	$\gamma_2(\times 10^2)$	$\delta_1$	$\delta_2$	Rank		Unconditional volatility	
															LBTSSR	LBTSSR	Pre	Post
LIC Housing Finance Ltd.	GJR	4.92**	0.06***	0.23***	2.72***	0.08***	0.73***	-2.32***	-1.87	15.58***	12.63***	-5.14			24.28*	16.63	1E-04	-0.03
Larsen & Toubro Ltd.	GJR	1.26	0.03**	0.39***	1.5***	0.05***	0.78***	-0.73**	0.89	4.91	14.1***	-0.87			14.65	10.97	9E-05	0.011
Lupin Ltd.	GJR	4.31*	0.07***	0.16***	0.76***	0.05***	0.86***	-0.16	0.91	2.02	10.98***	-0.39			32.4***	17.14	9E-05	0.01
Mahanagar Telephone Nigam Ltd.	GJR	8.61***	0.04**	0.29***	2.14***	0.07***	0.8***	-1.26***	0.31	0.26	5.83**	9.96***			20.15	10.66	2E-04	0.004
Mahindra & Mahindra Ltd.	GJR	4.42**	0.03*	0.31***	1.47***	0.06***	0.86***	-1.04***	2.49	-0.42	3.07	2.91			22.65*	10.73	2E-04	0.026
Matrix Laboratories Ltd.	GJR	4.61*	0.11***	0.07***	0.92***	0.07***	0.85***	-0.25	-0.37	0.07	8.95***	6.08			34.6***	25.93**	1E-04	-0
Mphasis Ltd.	GJR	4.09*	0.07***	0.15***	0.65***	0.08***	0.86***	-0.14	-3.8*	1.84	7.99***	6.84**			28.98**	24.76*	1E-04	-0.04
Nagarjuna Construction Company Ltd.	GJR	3.62	0.05**	0.15***	1.03***	0.09	0.82***	-0.07	-2.77	-1.48	10.84***	15.84***			17.7	12.66	1E-04	-0.03
Nagarjuna Fertilizers & Chemicals Ltd.	Power	4.55*	0.04***	0.22***	8.43***	-8.45	0.28***	-32***	0.15***	3.99	-11.47***	7.71***			30.54**	25.27**	1.279	2E-05
National Aluminium Company Ltd.	GJR	4.99**	0.08***	0.2***	0.62***	0.06***	0.9***	0.16	-0.67	-8.22***	3.93**	16.36***			20.66	13.58	1E-04	-0.01
Neyveli Lignite Corporation Ltd.	GJR	5.29**	0.06*	0.15***	0.38***	0.09***	0.87***	0.07	-3.47	-0.8	6.93***	7.72**			25.24**	16.94	1E-04	-0.04
Patel Engineering Ltd.	GJR	4.21	0.06***	0.14***	2.04***	0.05**	0.74***	-1.21***	-0.21	8.66**	19.89***	5.31			18.14	11.41	1E-04	-0
Rajesh Exports Ltd.	GJR	5.61**	0.06**	0.11***	0.82***	0.06***	0.84***	-0.31	3.16	2.41	10.05***	-2.06			15.11	7.38	9E-05	0.036
Ranbaxy Laboratories Ltd.	GJR	6.37***	0.05***	0.27***	1.8***	0.03**	0.86***	-1.21***	3.46*	-0.59	6.64***	3.86			35.67***	18	2E-04	0.038
Reliance Capital Ltd.	GJR	4.26**	0.02*	0.31***	0.75***	0.08***	0.86***	-0.07	0.11	-1.42	3.8**	4.36			13.64	13.15	1E-04	0.001
Reliance Industries Ltd.	GJR	0.35	0.06***	0.49***	1.31***	0.1***	0.81***	-0.32	-4.2*	-6.73**	3.81	21.27***			20.4	8.74	1E-04	-0.05

Reliance Mediaworks Ltd.	GJR	6.44***	0.04**	0.18***	1.37***	0.06**	0.76***	-0.93***	4.41	10.74***	17.12***	-11.64**	17.52	8.16	8E-05	0.057
Rolta India Ltd.	GJR	4.71**	0.05***	0.21***	0.51***	0.06***	0.87***	-0.13	0.88	2.79	8.29***	-2.67	31.63***	22.54*	8E-05	0.01
S Kumars	GJR	4.95*	0.09***	0.07***	0.96***	0.08***	0.84***	-0.3	-0.45	3.91*	9.98***	-0.44	24.07*	10.48	1E-04	-0.01
Nationwide Ltd.	GJR	3.96**	0.11***	0.22***	0.83***	0.06***	0.89***	-0.5**	11.36***	-6.53***	3.83*	1.12	24.85*	13.16	1E-04	0.111
Services Ltd.	GJR	4.47*	0.07***	0.13***	1.1***	0.07***	0.81***	-0.51**	1.63	5.59**	14.1***	-4.98	26.35**	17.63	9E-05	0.02
Shree Cement Ltd.	Power	1.22	0.04**	0.27***	0.84	0.07***	0.95***	4.84	4.05***	-6.1***	-14.85**	-24.06**	27.78**	18.75	7E-04	2E-05
Siemens Ltd.	GJR	2.69	0.04***	0.43***	3.89***	0.1***	0.59***	-3.09***	-1.83***	21.17***	22.64***	-12.09**	13.26	10.15	1E-04	-0.03
State Bank of India	GJR	4.28**	0.07***	0.23***	0.57***	0.07***	0.86***	0.57	4.25	-4.28	11.03***	3.51	25.6**	18.89	7E-05	0.046
Steel Authority of India Ltd.	GJR	7.02***	0.05***	0.18***	1.38***	0.05***	0.76***	-0.82***	2.63	11.2***	16.86***	-9.29**	21.9	15.59	7E-05	0.034
Sterlite Technology Ltd.	GJR	3.91	0.08***	0.2***	0.92***	0.05	0.86***	-0.41**	1.47	0.79	10.05***	1.61	26.27**	25.05**	1E-04	0.017
Sun Pharmaceutical Industries Ltd.	GJR	5.08**	0.04**	0.25***	1.27***	0.08***	0.78***	-0.75**	-0.65	6.93**	15.55***	-4.64	18.06	12.69	9E-05	-0.01
Syndicate Bank	GJR	4.46**	0.05***	0.2***	0.64***	0.06***	0.86***	-0.26*	-1.23	2.31	10.86***	0.6	26.37**	21.28	8E-05	-0.01
TVS Motor Company Ltd.	GJR	4.38**	0.06***	0.28***	1.12***	0.06***	0.85***	-0.65***	1.27	1.66	7.58***	3.28	35.75***	23.24*	1E-04	0.014
Tata Chemicals Ltd.	GJR	4.27**	0.05***	0.32***	1.35***	0.06***	0.86***	-0.97***	1.33	0.12	4.12***	4.67	15.21	11.02	2E-04	0.014
Tata Motors Ltd.	GJR	3.91*	0.04***	0.33***	2.58***	0.05***	0.81***	-2.21***	0.98	8.11**	9.68***	-3.08	21.29	11.31	2E-04	0.012
Company Ltd.	GJR	3.56*	0.06***	0.36***	1.36***	0.06***	0.85***	-1.04***	0.9	2.52	4.72**	1.74	21.83	14.95	2E-04	0.01
Tata Steel Ltd.	GJR	5.15**	0.04***	0.32***	0.76**	0.05***	0.92***	-0.34	4.14*	-5.39**	-0.94	5.75**	20.58	7.09	3E-04	0.04
Tata Tea Ltd.	GJR	7.39***	0.05**	0.2***	1.37***	0.06***	0.78***	-1.05***	-0.05	12.22***	13.57***	-6.67*	22.64*	18.84	9E-05	-0
Tata Teleservices (Maharashtra) Ltd.	GJR	3.93***	0.07***	0.17***	0.84***	0.07***	0.86***	-0.51***	-1.32	2.79*	8.43***	2.69	20.4	16.24	1E-04	-0.02
Titan Industries Ltd.	GJR	5.34**	0.04**	0.22***	1.1***	0.04***	0.82***	-0.74***	3.73	5.52	12.01***	-5.51	32.43***	17.16	8E-05	0.044
Vijaya Bank	GJR	2.54	0.05***	0.18***	1.19***	0.06***	0.83***	-0.52*	2.15	2.62	11.18***	-0.93	24.47*	14.8	1E-04	0.025
Voltas Ltd.	GJR	3.62*	0.1***	0.27***	0.17***	0.08***	0.91***	0.1	-2.13	-2.13	1.64***	7.06***	29.45**	21.43	2E-04	-0.02
Wipro Ltd.	GJR	5.72**	0.06***	0.23***	1.5***	0.04***	0.83***	-1.07***	3.83*	4.05*	13.21***	-3.29	32.15***	21.2	1E-04	0.045
Wockhardt Ltd.	GJR	4.65**	0.07***	0.18***	0.61***	0.07***	0.86***	-0.05	-1.58	-0.25	9.46***	9.21**	17.11	15.79	8E-05	-0.02
Zee Entertainment Enterprises Ltd.	GJR															

*Notes:* An illustrative case: ABB Limited – the estimates of  $\theta_1$  and  $\theta_2$  (pertaining to the mean Equation 4 reveal that ABB Ltd.'s stock returns are autoregressive ( $\theta_1$  is significant) and unaffected by the return on market portfolio ( $\theta_2$ ) is not significant. A GJR GARCH (1,1) specification of conditional volatility is found to be most appropriate based on the NIC for ABB Ltd. (see Fig. 4 in conjunction with Fig. 2).  $\alpha_1 > \beta_1$  implies that the 'news' coefficient ( $\alpha_1$ ) has decreased to ( $\beta_1$ ) in the post-derivative regime. Similarly,  $\alpha_2 > \beta_2$  implies that the 'persistence' coefficient ( $\alpha_2$ ) has decreased to ( $\beta_2$ ),  $\gamma_1 > \gamma_2$  implies that the degree of asymmetric response has declined. Of course, with  $\gamma_2$  being not significant for ABB Ltd. It means that asymmetric response is resolved in the post-derivatives regime.  $\delta_1$  and  $\delta_2$  are positive exponents of the PGARCH (1,1) specification. LBTSSR tests for the presence of autocorrelation in squared standardized residuals of a GARCH model. The null hypothesis is the absence of autocorrelation. In the case of ABB Ltd. The switching GJR GARCH(1,1) specification does not seem to be adequate. The unconditional volatility seems to have decreased in the case of ABB Ltd. after a derivative trading is introduced. LBTSSR and LBTSSR stand for LB Test of standardized residuals and squared standardized residuals, respectively. They test for existence of autocorrelation in standardized and squared standardized residuals. Test statistic is distributed as  $\chi^2(12)$  and tests the null hypothesis of absence of autocorrelation. \*\*\*, \*\* and \* indicate test statistic significance at 1, 5 and 10% levels, respectively.

Change due to introduction of derivatives trading	Impact of old information on conditional volatility <b>decreases</b> post introduction of derivatives trading $\alpha_2 < \beta_2$	Impact of old information on conditional volatility <b>increases</b> post introduction of derivatives trading $\alpha_2 > \beta_2$
New Information is impounded in stock prices at a <b>faster</b> rate post introduction of derivatives trading. $\alpha_1 < \beta_1$		28 companies
New Information is impounded in stock prices at a <b>slower</b> rate post introduction of derivatives trading. $\alpha_1 > \beta_1$		73 companies

**Fig. 3. Summary of the change in structure of conditional volatility post introduction of derivatives trading**

If the proportion of noise traders in the derivatives market is higher than the informed speculators, then not all signals emanating from the derivative market contain relevant information. Thus, while a lot of information is being generated and sent to the spot market (from the derivatives market), since the quality of such information is in question, the investors in the spot market may use only a part of this ‘new’ information. Such may be the case in India, because volumes in Indian derivatives market are dominated by individual stock derivative instruments (Appendix 1) which are not a cost effective way to hedge. Also, most of these trades are executed by retail participants (Appendix 2) and despite reforms, the retail investor remains the most informationally disadvantaged, especially with regard to information that can be used in the short run (National Stock Exchange, 2001–2010). Retail investors are still concerned about management frauds, lack of transparency, price manipulations and volatility. If such investors trade in the derivatives market, wherein the maximum tenure for a trade position is 3 months, the signals that so emanate may not be rich in relevant information.

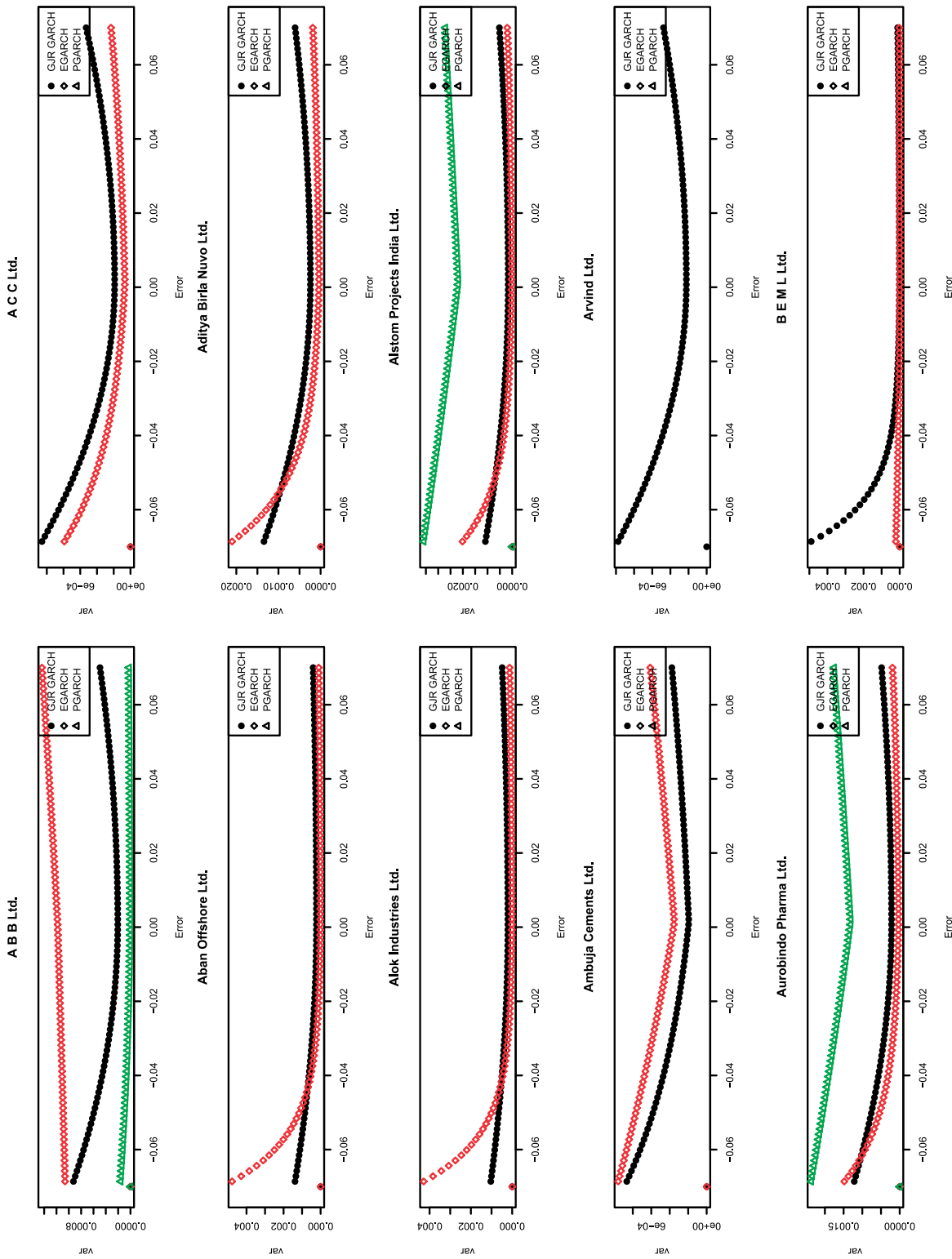
## V. Conclusion

This article first confirms the existence of a change in the structure of conditional stock return volatility around the time when futures and options trading on these stocks were introduced (Table 2). Since futures and options trading was introduced at the same time, in the case of most stocks, the exact point of regime

change is known. Hence, alternative SAGARCH (1, 1) models, for each stock, are specified and the final choice of model is made based on the NIC (Fig. 4) and the goodness-of-fit (Table 3). Thereafter, an analysis of the unconditional variance in the two regimes is conducted. It is seen that there is an increase in unconditional variance in the post-derivative regime hinting at a rise in flow of information in most stocks, post introduction of derivatives trading. Such information, in the absence of noise traders in the spot market and few noise traders in the derivatives market, should result in a decrease in persistence, an increase in the rate of absorption of ‘new’ information and symmetric response (if asymmetry was due to noise traders) of stock return volatility.

However, it is seen that in the case of most of the stocks analysed, derivatives trading seems to have reduced both ‘persistence’ as well as the rate of absorption of ‘new’ information. Also, post-derivatives asymmetric response is not removed completely. Such a phenomenon, it is reasoned, may be because of the poor quality of information that is generated in the derivative market. This is probable, because in the Indian derivative markets, most of the volumes (till recently) are grossed by individual stock (mostly stock futures) derivative instruments (Appendix 1) and most of these trades are executed by retail investors (Appendix 2). If the purpose of such trades is to hedge, then individual stock futures are an expensive way to hedge and if the purpose is to speculate, then the retail investor may not have the information advantage needed to make trading gains in the short run. The retail investor, based on his analysis, wisdom and observation, may create





**Fig. 4. News impact curve for switching EGARCH(1,1), PGARCH(1,1) and GJR GARCH(1,1) models**

*Notes:* Figure 4 reports the NIC for each stock analysed. There is a unique NIC for each switching asymmetric GARCH (1,1) specification (EGARCH, PGARCH and GJR GARCH). Thus, for each stock, there would be at most three NICs. However, there can be lesser number of NICs if one or more of the GARCH log likelihood functions do not converge to a solution. The Y-axis of an NIC depicts the conditional volatility and the X-axis gives the information impulse.

An illustrative case: ABB Limited – NIC for ABB Limited reveals the following: (i) The switching EGARCH (1,1) NIC does not capture the asymmetry and it seems to show that the volatility increases linearly as one moves from ‘bad’ to ‘good’ news, (ii) The PGARCH (1,1) NIC is able to capture asymmetry but does not adequately capture the response of conditional volatility to ‘good’ news, (iii) The GJR GARCH (1,1) NIC seems to capture both the asymmetric response as well as the response of conditional volatility to ‘good’ news. Thus, the Switching GJR GARCH (1,1) model is specified for this company. In general, the process followed for final model specification is detailed in a flow chart given in Fig. 2.

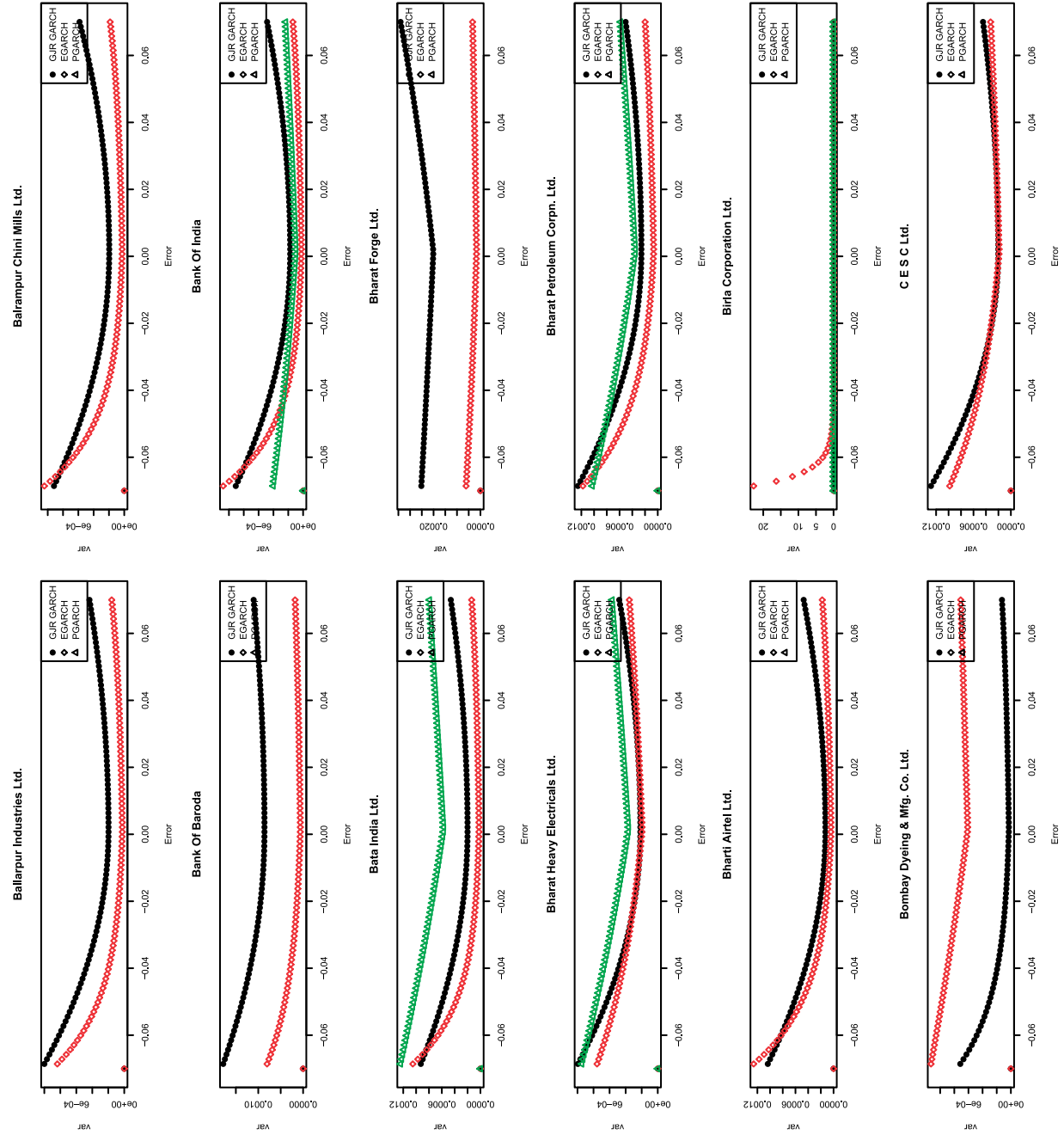


Fig. 4. Continued

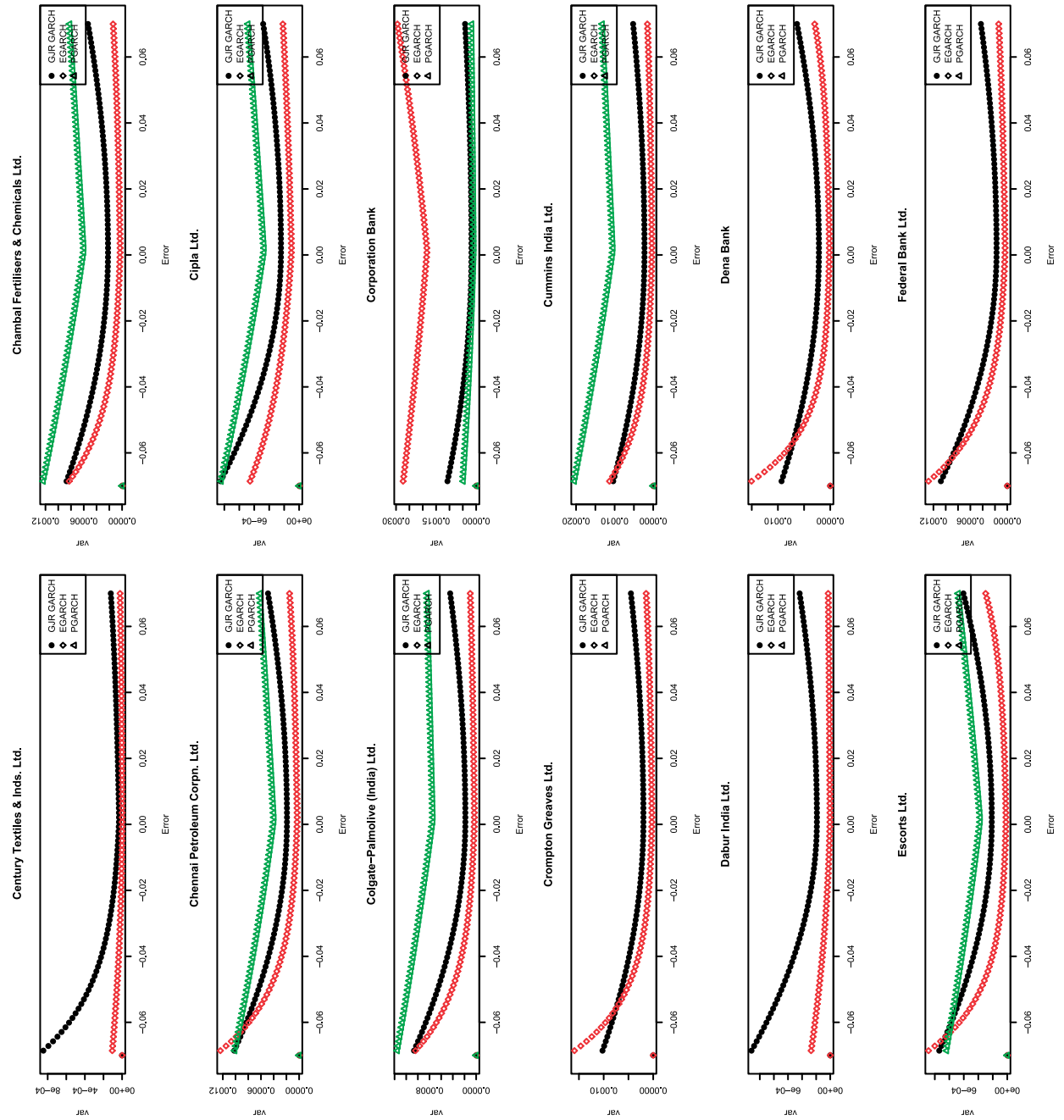


Fig. 4. Continued

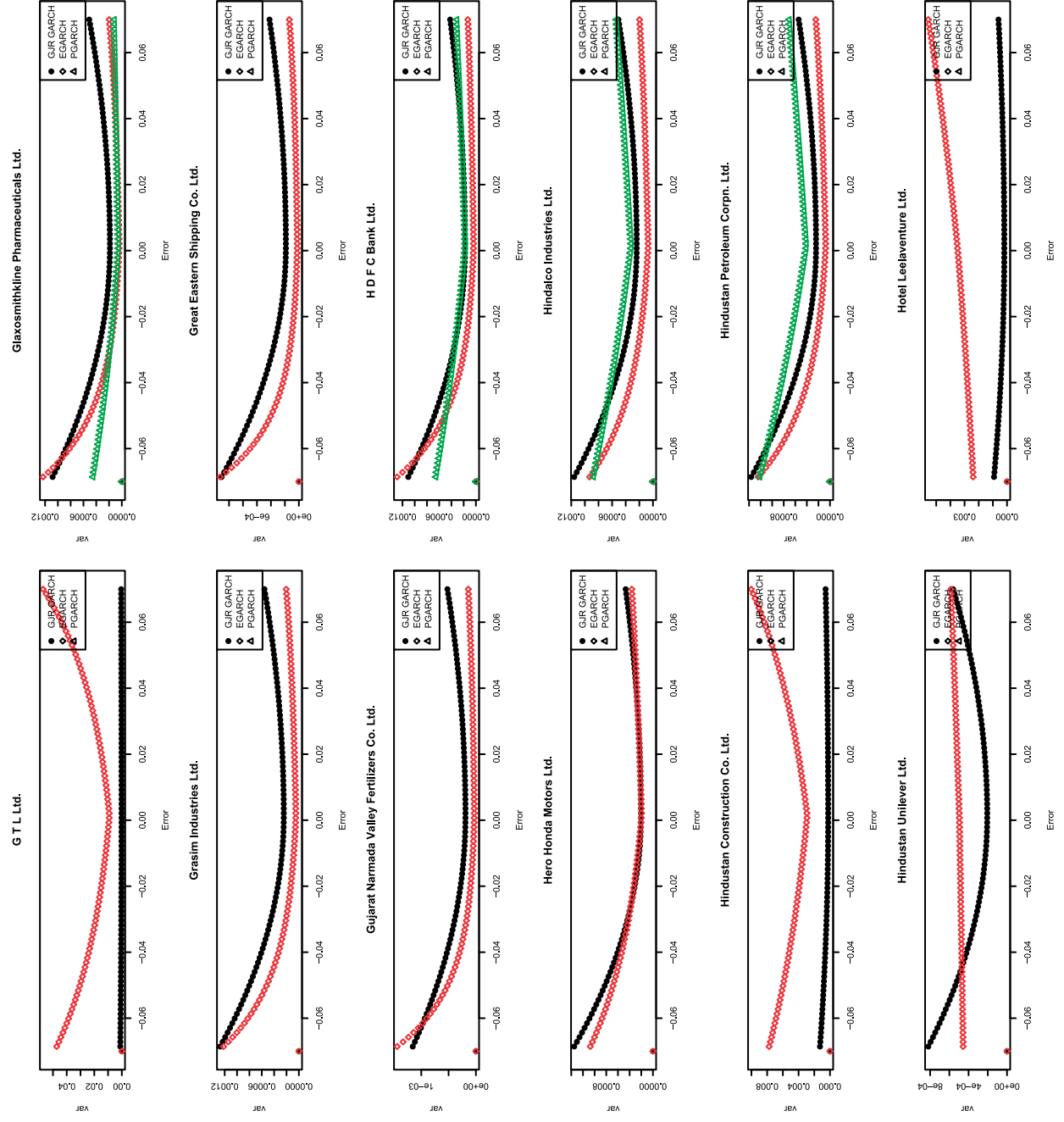


Fig. 4. Continued

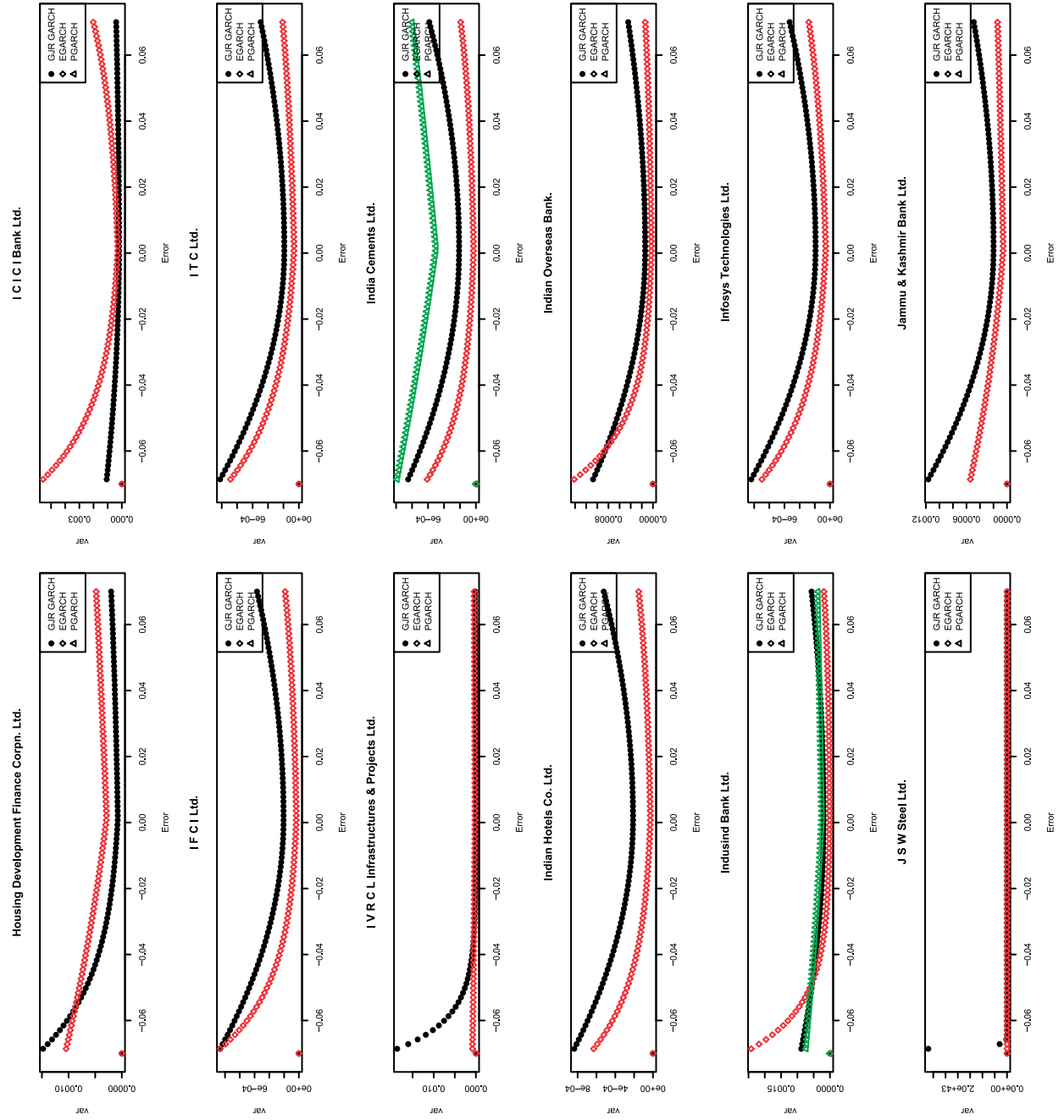


Fig. 4. Continued

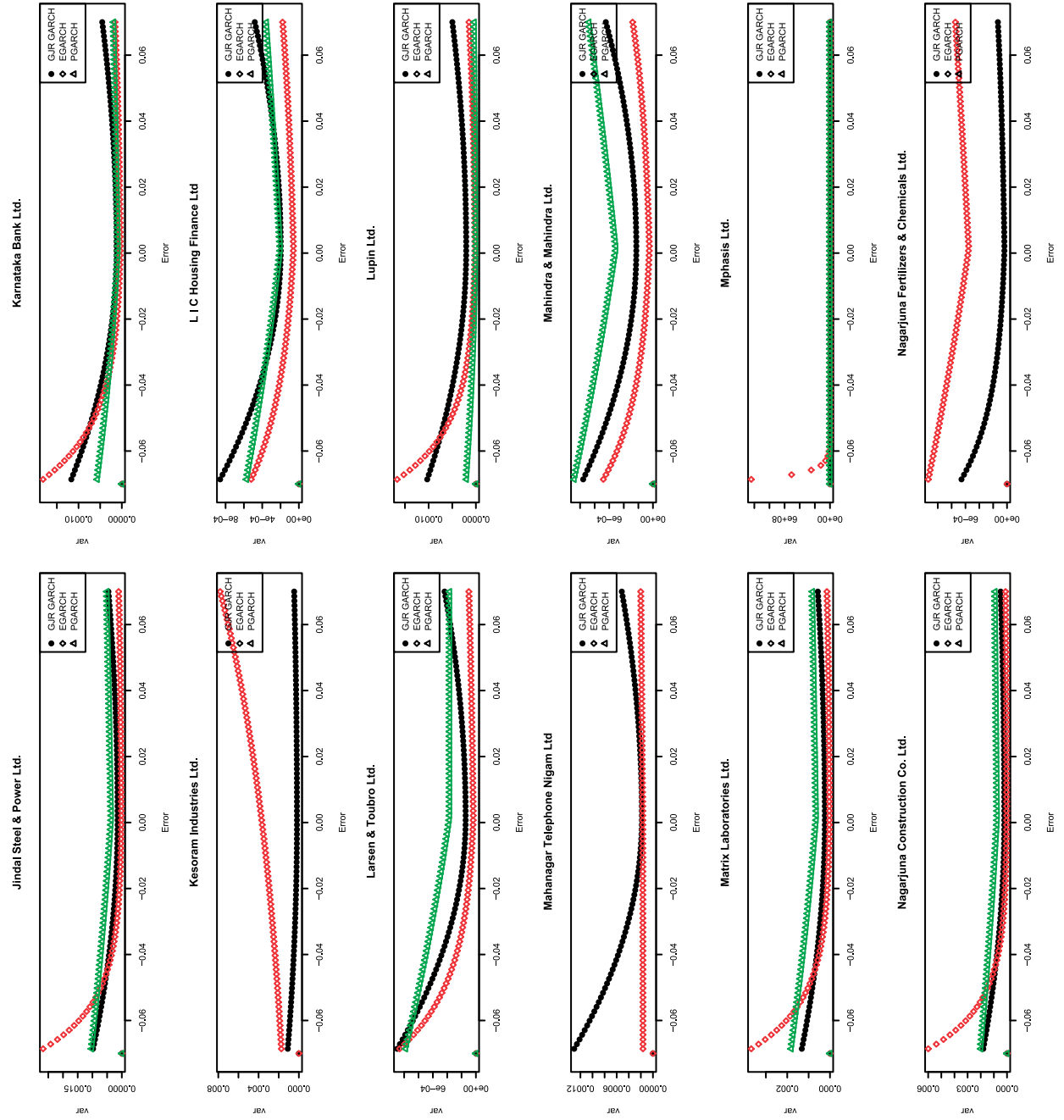


Fig. 4. Continued

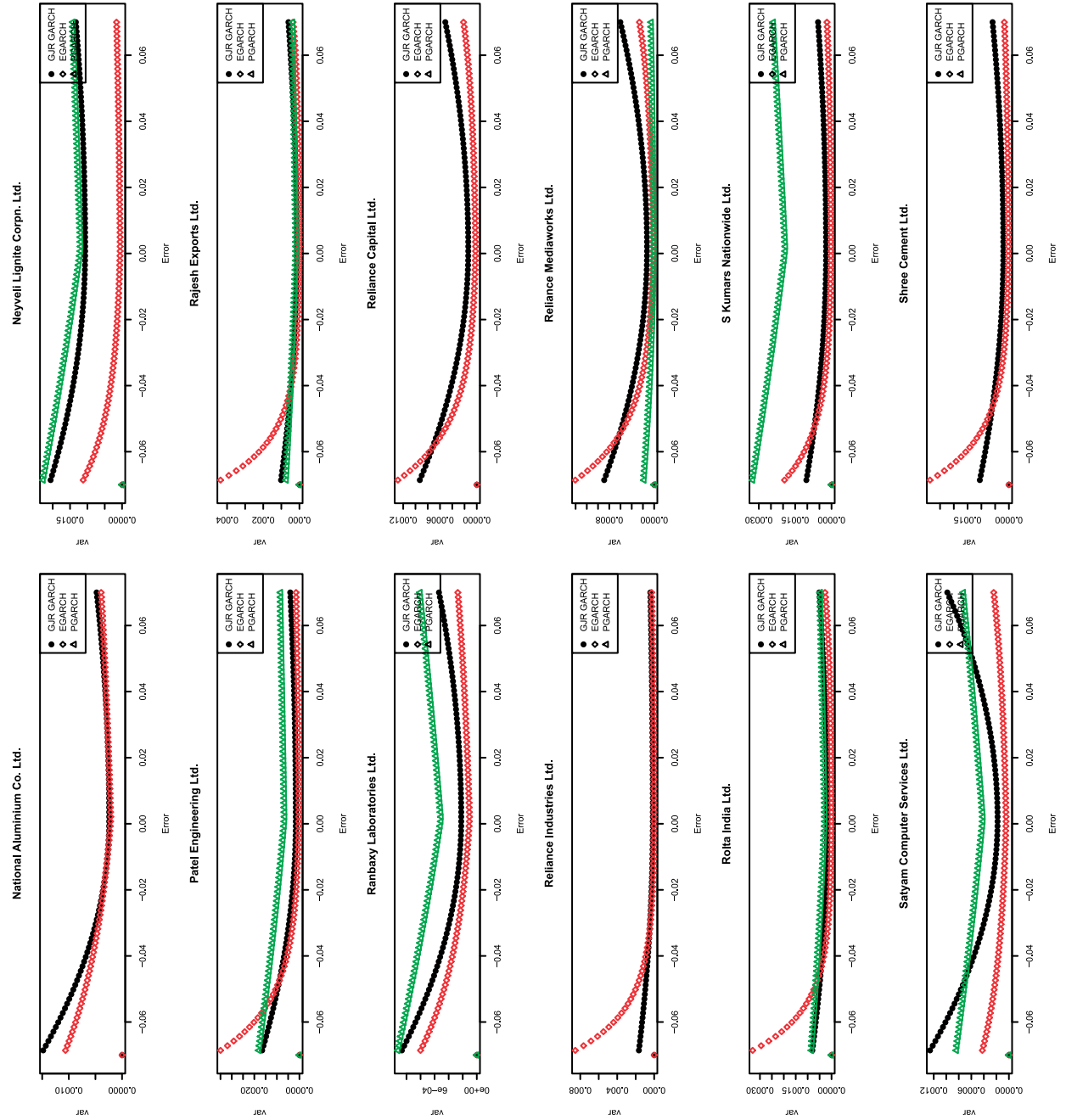


Fig. 4. Continued

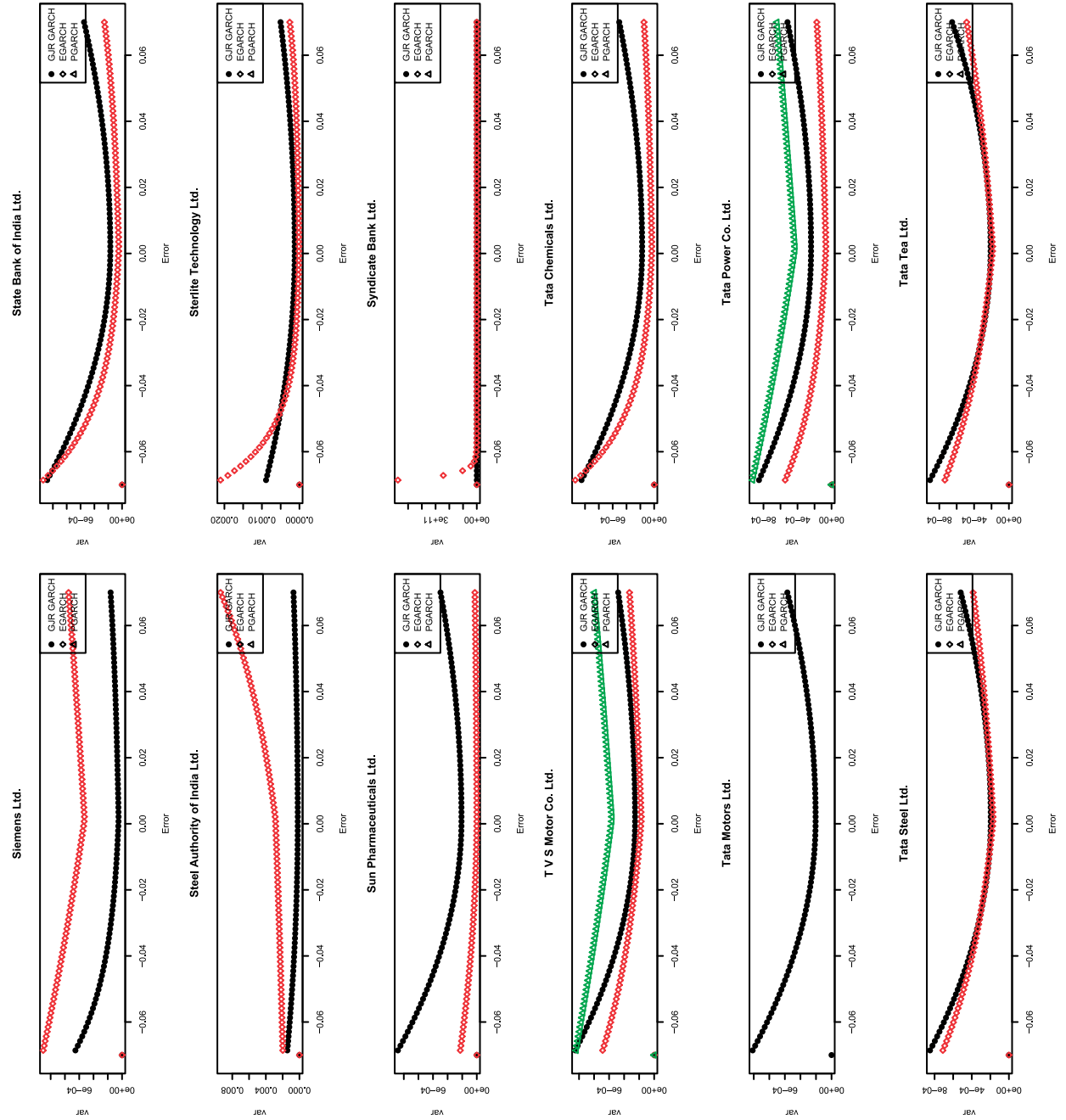


Fig. 4. Continued



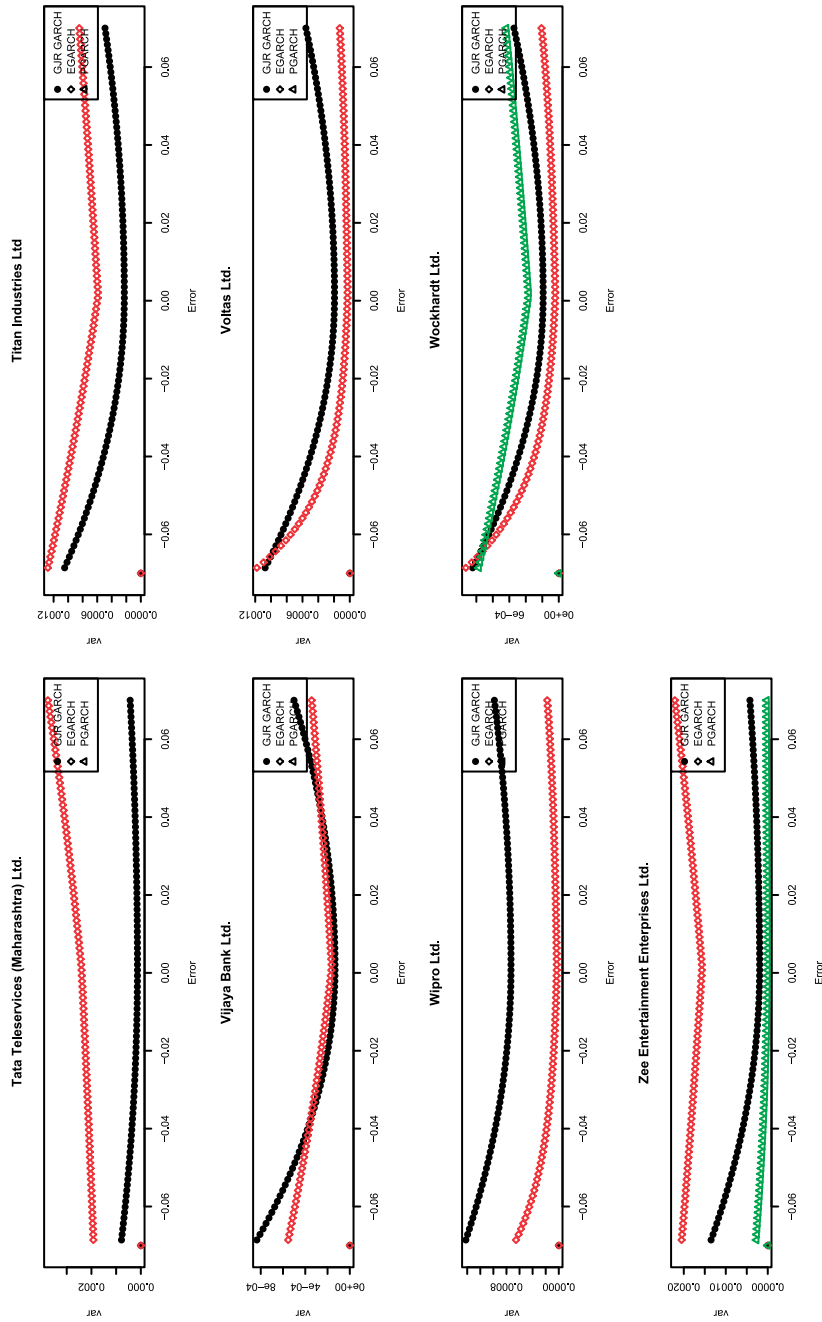


Fig. 4. Continued

information regarding the long-term trends of a stock. But as far as such information that can be used in a short period of time is concerned, retail investors may not possess the informational advantage. In the Indian stock derivatives market, it is possible to take trade positions only for a maximum period of 3 months. Considering that individual stock derivative instruments will form a significant part of the volumes traded and much of these trades will be executed by retail investors, this article builds a case for introduction of longer term derivative instruments (for periods more than 3 months). Such instruments would attract more meaningful retail participation, thus reducing the proportion of noise traders in the derivatives market.

### Acknowledgements

I am grateful to an anonymous referee whose comments greatly enriched the quality of this article. Further, I acknowledge with thanks the help provided by Jyotirmoy while writing the code in R and the discussions with Prof. Krish Ladha that contributed to the development of this article. The usual disclaimer applies to all remaining errors and omissions

### References

- Aggarwal, R., Inclan, C. and Leal, R. (1999) Volatility in emerging stock markets, *Journal of Financial and Quantitative Analysis*, **34**, 33–55.
- Antoniou, A. and Holmes, P. (1995) Futures trading, information and spot price volatility: evidence from FTSE-100 stock index futures contracts using GARCH?, *Journal of Banking and Finance*, **19**, 117–29.
- Antoniou, A., Holmes, P. and Priestley, R. (1998) The effects of stock index futures trading on stock index volatility: an analysis of the asymmetric response of volatility to news?, *The Journal of Futures Markets*, **18**, 151–66.
- Bandivadekar, S. and Ghosh, S. (2003) Derivatives and volatility on Indian stock markets, *Reserve Bank of India Occasional Papers*, **23**, 187–201.
- Bekaert, G. and Wu, G. (2000) Asymmetric volatility and risk in equity markets, *The Review of Financial Studies*, **13**, 1–42.
- Black, F. (1976) Studies in stock price volatility changes, in *Proceedings of the 1976 Meeting of the American Statistical Association, Business and Economics Statistics Section*, American Statistical Association, pp. 177–81.
- Black, F. (1986) Noise, *Journal of Finance*, **41**, 529–43.
- Bollerslev, T. (1986) Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics*, **33**, 307–27.
- Bologna, P. and Cavallo, L. (2002) Does the introduction of stock index futures effectively reduce stock market volatility? Is the 'Futures Effect' immediate? Evidence from the Italian stock exchange using GARCH, *Applied Financial Economics*, **12**, 183–92.
- Burns, P. (2002) Robustness of the Ljung Box test and its rank equivalent. Available at <http://www.burns-stat.com/pages/Working/ljungbox.pdf> (accessed 28 October 2007).
- Butterworth, D. (2000) The impact of futures trading on underlying stock index volatility: the case of the FTSE mid 250 contract, *Applied Economics Letters*, **7**, 439–42.
- Campbell, J. Y. and Hentschel, L. (1992) No news is good news: an asymmetric model of changing volatility in stock returns, *Journal of Financial Economics*, **31**, 281–318.
- Christie, A. (1982) The stochastic behaviour of common stock variance: value, leverage and interest rate effects, *Journal of Financial Economics*, **10**, 407–32.
- Dennis, S. A. and Sim, A. B. (1999) Share price volatility with the introduction of individual share futures on the Sydney futures exchange, *International Review of Financial Analysis*, **8**, 153–63.
- Ding, Z., Granger, C. W. J. and Engle, R. F. (1993) A long memory property of stock market returns and a new model, *Journal of Empirical Finance*, **1**, 83–106.
- Engle, R. F. (1982) Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation, *Econometrica*, **50**, 987–1007.
- Engle, R. F. and Ng, V. K. (1993) Measuring and testing the impact of news on volatility, *Journal of Finance*, **48**, 1749–78.
- Fama, E. F. (1965) The behaviour of stock market prices, *Journal of Business*, **38**, 34–105.
- Fernandez, V. (2006) Structural break points in volatility in international markets, *Economic Systems*, **30**, 79–97.
- French, K. R., Schwert, G. W. and Stambaugh, R. (1987) Expected stock returns and volatility, *Journal of Financial Economics*, **19**, 3–29.
- Glosten, L. R., Jagannathan, R. and Runkle, D. E. (1993) On the relations between the expected value and the volatility of the nominal excess returns on stocks, *Journal of Finance*, **48**, 1779–91.
- Gulen, H. and Mayhew, S. (2000) Stock index futures trading and volatility in international equity markets, *The Journal of Futures Markets*, **20**, 661–85.
- Henry, O. (1998) Modelling the asymmetry of stock market volatility, *Applied Financial Economics*, **8**, 145–53.
- Inclan, C. and Tiao, G. (1994) Use of cumulative sums of squares for retrospective detection of changes in variance, *Journal of American Statistical Association*, **89**, 913–23.
- Kassimatis, K. (2002) Financial liberalization and stock market volatility in selected developing countries, *Applied Financial Economics*, **12**, 389–94.
- Kim, D. and Kon, S. J. (1994) Alternative models for the conditional heteroskedasticity of stock returns, *Journal of Business*, **67**, 563–98.
- Lee, S. B. and Ohk, Y. K. (1992) Stock index futures listing and structural change in time-varying volatility, *The Journal of Futures Markets*, **12**, 493–509.
- Mandelbrot, B. (1963) The variation of certain speculative prices, *Journal of Business*, **36**, 394–419.
- Nath, G. C. (2003) Behaviour of stock market volatility after derivatives. Available at <http://www.nse-india.com/content/press/nov2003a.pdf> (accessed 2 September 2007).

- National Stock Exchange of India Ltd (2001–2010). *Factbook*, various issues, National Stock Exchange of India Ltd, Mumbai.
- Nelson, D. (1991) Conditional heteroskedasticity in asset returns: a new approach, *Econometrica*, **59**, 347–70.
- Pagan, A. and Schwert, G. (1990) Alternative models for common stock volatility, *Journal of Econometrics*, **45**, 267–90.
- Percival, D. and Walden, A. (2000) *Wavelet Methods for Time Series Analysis*, Cambridge University Press, Cambridge.
- Pilar, C. and Rafael, S. (2002) Does derivatives trading destabilize the underlying assets? Evidence from the Spanish stock market, *Applied Economics Letters*, **9**, 107–10.
- Pindyk, R. S. (1984) Risk, inflation and the stock market, *American Economic Review*, **74**, 334–51.
- Pok, W. C. and Poshakwale, S. (2004) The impact of the introduction of futures contracts on the spot market volatility: the case of Kuala Lumpur stock exchange, *Applied Financial Economics*, **14**, 143–54.
- Ryoo, H. J. and Smith, G. (2004) The impact of stock index futures on the Korean stock market, *Applied Financial Economics*, **14**, 243–51.
- Securities Exchange Board of India (2008) Report: Derivatives Market Review Committee [Online], Securities Exchange Board of India. Available at <http://www.sebi.gov.in/commreport/derivativerep.pdf> (accessed 10 October 2010).
- Shenbagaraman, P. (2003) Do futures and options trading increase stock market volatility? [Online], NSE Working Paper No. 20. Available at <http://www.nseindia.com/content/research/Paper60.pdf> (accessed 8 June 2007).
- Vipul (2006) Impact of introduction of derivatives on underlying volatility: evidence from India, *Applied Financial Economics*, **16**, 687–97.
- Zivot, E. (2009) Practical issues in the analysis of univariate GARCH models, in *Handbook of Financial Time Series* (Eds) T. G Anderson, R. A. Davis, J.-P. Kreiß and T. Mikosch, Springer-Verlag, Berlin, Heidelberg, pp. 113–55.

## Appendix 1

*Productwise futures and options turnover (% of total)*

Year	Index futures	Individual stock futures	Index options	Individual stock options
2001 to 2002	21.08	50.54	3.69	24.69
2002 to 2003	9.99	65.14	2.10	22.76
2003 to 2004	26.03	61.30	2.48	10.20
2004 to 2005	30.32	58.27	4.79	6.63
2005 to 2006	31.38	57.87	7.02	3.74
2006 to 2007	34.52	52.08	10.77	2.63
2007 to 2008	28.21	58.83	2.84	10.12
2008 to 2009	32.42	31.60	33.89	2.08
2009 to 2010	22.27	29.41	45.45	2.87

Source: Factbook, NSE (various issues).

## Appendix 2

*Product participant wise futures and options turnover (% of total)*

Year	Institutional	Retail	Proprietary
2007 to 2008	12	63	25
2008 to 2009	13.37	55.63	31
2009 to 2010	13.51	54.86	31.63

Source: Factbook, NSE (various issues).

## Appendix 3

*Code used in the analysis (in R)*

```
require(maxLik)
require(FinTS)
#Common code
```

```
llhgen <- function(core,y,x,d){
llh <- function(param){
  uh <- -core(y,x,d,param)
  u <- uh$u
  u2 <- u**2
  h <- uh$h
  N <- length(h)
  val.vec = (-0.5*log(h[2:(N-1)]
    -0.5*(u2[2:(N-1)]/h[2:(N-1)]))
  val.vec [is.na(val.vec)||!is.finite(val.vec)] = NA
  return(val.vec)}
return(llh)}
estimate <- function(core,y,x,d,init){
llh <- llhgen(core,y,x,d)
o <- -maxBHHH(llh,start = init, iterlim = 1000)
if (o$code >= 3)
stop("Maximum likelihood did not converge")
OI <- -solve(o$hessian)
se <- sqrt(diag(-OI))
t <- o$estimate/se
pval <- -2*(1-pt(abs(t), 1000))
uh <- -core(y,x,d,o$estimate)
return(list(estimate = o$estimate, se = se, t = t,
pval = pval, sqrresid = uh$u, stdsqresid = uh$u/
uh$h, uncvar = uh$h[1]))}
#####GJR
Code#####
###
core.gjr <- function(y,x,d,param){
a <- -param[1]
b <- -param[2]
c <- -param[3]
a1 <- -param[4]
a2 <- -param[5]
```

```

al3 <- param[6]
bl1 <- param[7]
bl2 <- param[8]
bl3 <- param[9]
g1 <- param[10]
g2 <- param[11]
N = length(y)
u <- -(y[2:N]-a-b*y[1:(N-1)]-c*x[2:N])
u2 <- -u**2
h <- numeric(N-1)
h[1] = al1/(1-al2-al3-0.5*g1)
for(i in 2:(N-1)){
  h[i] = (al1 + d[i]*bl1) + (al2 + d[i]*bl2)*u2[i-1]
  + (al3 + d[i]*bl3)*h[i-1]
  if(u[i-1] < 0)
    h[i] = h[i] + g1*u2[i-1] + g2*d[i]*u2[i-1]
  return(list(u = u,h = h))
}
do.gjr <- function(x){
  init <- c(1.500986e-04, 9.793117e-03, 1.173565e + 00,
  8.282873e-05, 1.349993e-01, 7.856720e-01, 4.865471e-
  05, 3.972743e-02, 3.880092e-02, 3.260417e-02,
  6.602367e-02)
  gjr <- estimate(core.gjr,x[,3],x[,2],x[,4],init)
  a0 <- (gjr$estimate[4] + gjr$estimate[7])
  b1 <- (gjr$estimate[6] + gjr$estimate[9])
  return(c(gjr, a0 = a0, a1 = (gjr$estimate[5] + gjr$esti-
  mate[8]), b1 = b1, g = (gjr$estimate[10] + gjr$esti-
  mate[11]), A = a0 + b1*gjr$uncvar))
}
nic.gjr <- function(gjr,epsilon){
  N <- length(epsilon)
  sigma2 <- numeric(N)
  for(i in 2:N){sigma2[i] = gjr$A + (gjr$a1 + gjr$g*
  (epsilon[i-1] < 0))*epsilon[i-1]^2} sigma2}
#####Egarch
Code#####
core.egarch <- function(y,x,d,param){
  a <- param[1]
  b <- param[2]
  c <- param[3]
  al1 <- param[4]
  al2 <- param[5]
  al3 <- param[6]
  bl1 <- param[7]
  bl2 <- param[8]
  bl3 <- param[9]
  g1 <- param[10]
  g2 <- param[11]
  N = length(y)
  u <- -(y[2:N]-a-b*y[1:(N-1)]-c*x[2:N])
  u2 <- -u**2
  h <- numeric(N-1)
  h[1] = exp(((al1-al3*(2/pi)^0.5)/(1-
  al2)) + 0.5*((al3^2 + g1^2)/(1-al2^2)))

```

```

for(i in 2:(N-1)){
  h[i] = exp((al1 + d[i]*bl1) + (al2 + d[i]*bl2)*log(h[i-1]) +
  (al3 + d[i]*bl3)*((abs(u[i-1])/h[i-1]^0.5)-(2/pi)^0.5) +
  (g1 + d[i]*g2)*(u[i-1]/h[i-1]^0.5)))
  return(list(u = u,h = h))
}
do.egarch <- function(x){
  init <- c(1.500986e-04, 9.793117e-03, 1.173565e + 00,
  8.282873e-05, 1.349993e-01, 7.856720e-01, 4.865471e-
  05, 3.972743e-02, 3.880092e-02, 3.260417e-02,
  6.602367e-02)
  egarch <- estimate(core.egarch,x[,3],x[,2],x[,4],init)
  a0 <- (egarch$estimate[4] + egarch$estimate[7])
  a1 <- (egarch$estimate[5] + egarch$estimate[8])
  b1 <- (egarch$estimate[6] + egarch$estimate[9])
  g <- (egarch$estimate[10] + egarch$estimate[11])
  A <- ((egarch$uncvar)^a1)*exp(a0-b1*(2/pi)^0.5)
  return(c(egarch, a0 = a0,a1 = a1,b1 = b1,g = g,
  A = A))
}
nic.egarch <- function(egarch,epsilon){
  N <- length(epsilon)
  sigma2 <- numeric(N)
  uncsd <- sqrt(egarch$uncvar)
  for(i in 2:N){if (epsilon[i-1] >= 0)
    sigma2[i] = egarch$A*exp(((egarch$g + egarch$
  b1)/uncsd)*epsilon[i-1])
  else
    sigma2[i] = egarch$A*exp(((egarch$g-
  egarch$b1)/uncsd)*epsilon[i-1])}
  sigma2}
#####
PGARCH
Code#####
core.pgarch <- function(y,x,d,param){
  a <- param[1]
  b <- param[2]
  c <- param[3]
  al1 <- param[4]
  al2 <- param[5]
  al3 <- param[6]
  bl1 <- param[7]
  bl2 <- param[8]
  bl3 <- param[9]
  g1 <- param[10]
  g2 <- param[11]
  p1 <- param[12]
  p2 <- param[13]
  N = length(y)
  if(abs(g1 + g2) > 1)
  return(list(u = rep(Inf,N-1),h = rep(Inf,N-1)))
  u <- -(y[2:N]-a-b*y[1:(N-1)]-c*x[2:N])
  u2 <- -u**2
  h <- numeric(N-1)
  h[1] = (al1^2)/(1-al2*(2/pi)^0.5-al3^2)

```

```

x <- -p1 + d*p2
for(i in 2:(N-1)){
h[i] = ((a1 + d[i]*b1) + (a2 + d[i]*b2)*(abs(u[i-1]) + (g1 + d[i]*g2)*u[i-1])^x[i] + (a3 + d[i]*b3)
*(h[i-1]^(x[i]/2)))^(2/x[i]))
return(list(u = u,h = h))}
do.pgarch <- function(x){
init <- c(1.500986e-04, 9.793117e-03, 1.173565e + 00,
8.282873e-05, 1.349993e-01, 7.856720e-01, 4.865471e-05,
3.972743e-02, 3.880092e-02, 3.260417e-02,
6.602367e-02,1, 1)
pgarch <- estimate(core.pgarch,x[,3],x[,2],x[,4],init)
uncsd <- sqrt(pgarch$uncvar)
a0 <- (pgarch$estimate[4] + pgarch$estimate[7])
a1 <- (pgarch$estimate[5] + pgarch$estimate[8])
b1 <- (pgarch$estimate[6] + pgarch$estimate[9])
g <- (pgarch$estimate[10] + pgarch$estimate[11])
A <- (a0 + b1*uncsd)^2
return(c(pgarch,
a0 = a0,a1 = a1, b1 = b1,g = g,A = A))}
nic.pgarch <- function(pgarch,epsilon){
N <- length(epsilon)
sigma2 = numeric(N)
for(i in 2:N){error = abs(epsilon[i-1]) + pgarch$g*
epsilon[i-1]
sigma2[i] = pgarch$A + 2*sqrt(pgarch$A)*pgarch$
a1*error + (pgarch$a1*error)^2}
sigma2}
#####results and
plots#####
my.analysis <- function(filename,detailed.graph =
TRUE){cat(filename,"\n")
basename <- gsub('.csv',' ',filename)
N <- 100
epsilon = seq(-0.07,0.07,length = N)
x <- read.csv(filename,header = TRUE)
nicmat <- matrix(NA,N,0)
gjr.local <- function(){cat("***GJR**\n")
gjr <- do.gjr(x)
sigma2.gjr <- nic.gjr(gjr,epsilon)
nicmat <- cbind(nicmat,sigma2.gjr)
results.gjr <- cbind(gjr$estimate,gjr$se,gjr$t,
gjr$pval)
print(results.gjr,digits = 5)
gjr.ssr <- gjr$stdsqresid
lbt.gjr <- Box.test(gjr.ssr, lag = 15, type = "Ljung")
print(lbt.gjr)
rank.gjr <- AutocorTest(gjr.ssr,type =
c("rank"), df = 15)
print(rank.gjr)
if(detailed.graph==TRUE)
plot(epsilon,sigma2.gjr, type = "p",pch = 19, main =
paste("GJR GARCH NIC for",basename),
xlab = "Epsilon", ylab = "variance")
egarch.local <- function(){cat("\n\n**EGARCH**\n")
egarch <- do.egarch(x)
sigma2.egarch <- nic.egarch(egarch,epsilon)
nicmat <- cbind(nicmat,sigma2.egarch)
results.egarch <- cbind(egarch$estimate,egarch$
se,egarch$t,egarch$pval)
print(results.egarch, digits = 5)
egarch.ssr <- egarch$stdsqresid
lbt.egarch <- Box.test(egarch.ssr, lag = 15, type =
"Ljung")
print(lbt.egarch)
rank.egarch <- AutocorTest(egarch.ssr,type =
c("rank"), df = 15)
print(rank.egarch)
if(detailed.graph == TRUE)
plot(epsilon,sigma2.egarch, type = "p",pch = 23,
main = paste("EGARCH NIC for",basename),
xlab = "Epsilon", ylab = "variance")}
pgarch.local <- function(){
cat("\n\n**PGARCH**\n")
pgarch <- do.pgarch(x)
sigma2.pgarch <- nic.pgarch(pgarch,epsilon)
nicmat <- cbind(nicmat,sigma2.pgarch)
results.pgarch <- cbind(pgarch$
estimate,pgarch$se,pgarch$t,pgarch$pval)
print(results.pgarch, digits = 5)
pgarch.ssr <- pgarch$stdsqresid
lbt.pgarch <- Box.test(pgarch.ssr, lag = 15,
type = "Ljung")
print(lbt.pgarch)
rank.pgarch <-
AutocorTest(pgarch.ssr,type = c("rank"), df = 15)
print(rank.pgarch)
if(detailed.graph == TRUE)
plot(epsilon,sigma2.pgarch, type = "p",pch = 24,
main = paste("PGARCH NIC for",basename),
xlab = "Epsilon", ylab = "variance")}
try(gjr.local())
try(egarch.local())
try(pgarch.local())
print(dim(nicmat))
if (ncol(nicmat) > 0){matplot(epsilon, nicmat,
type = "p", pch = c(19,23,24), main = paste("News
Impact
Curves for",basename), xlab = "Epsilon", ylab =
"variance")
legend("topright", c("GJR GARCH", "EGARCH",
"PGARCH"), pch = c(19,23,24))}
eat.one <- function(f){sink(paste(f,'.txt',sep = ""))
win.metafile(paste(f,'_%d'.wmf',sep = ""))
try(my.analysis(f))
sink()}

```

```
    dev.off()
eat.directory <- function(){files <- list.files(pattern =
'.*\\.csv')
for (f in files){message("Processing ",f)
  eat.one(f)}}
eat.fancy <- function(){
  pdf('s_%d.pdf')
  par(mfrow = c(8,3),cex = 0.2)
```

```
files <- list.files(pattern = '.*\\.csv$')
for (f in files){
  message("Processing ",f)
  eat.one.fancy(f)
}
dev.off()
}
```