Modelling asymmetry and persistence under the impact of sudden changes in the volatility of the Indian stock market

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Abstract In this paper, we compare the performance of Inclan and Tiao's (IT) (1994) and Sanso, Arago and Carrion's (AIT) (2004) iterated cumulative sums of squares (ICSS) algorithms by means of Monte Carlo simulation experiments for various data-generating processes with conditional and unconditional variance. In addition, we investigate the impact of regime shifts on the asymmetry and persistence of volatility from the vantage point of modelling volatility in general and, in particular, in assessing the forecasting ability of the GARCH class of models in the context of the Indian stock market.
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Introduction

Volatility, in general, represents risk or uncertainty associated with an asset and, hence, exploring the behaviour of volatility of asset returns is relevant for the pricing of financial assets, risk management, portfolio selection, trading strategies and the pricing of derivative instruments (Poon & Granger, 2003). Existing literature recognises the time varying nature of the conditional volatility of the financial asset returns. The dynamic nature of volatility can be modelled by using the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) class of models (Engle, 1982 and Bollerslev, 1986) by specifying the conditional mean and conditional variance equations. Numerous extensions of GARCH models have been proposed in the literature. For instance, Engle and Bollerslev (1986) propose the Integrated GARCH (IGARCH) model to capture the impact of a shock on the future volatility over an infinite horizon. The EGARCH model (Nelson, 1991), GJR-GARCH model (Glosten, Jagannathan, & Runkle, 1993) and APARCH model (Ding, Granger, & Engle, 1993) are all popular models that can in addition capture the asymmetric behaviour of the volatility of returns. The Indian stock market has shown significant growth in the last decade and has made available enormous opportunities for market participants. Like in other emerging markets, investors in India also face higher risk. (See the higher

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weekly standard deviation as shown in Table 5.) Hence, it is essential to study the dynamic behaviour of the volatility of returns from the Indian stock market under the impact of sudden changes in volatility.

Volatility of the returns of financial assets may be affected substantially by infrequent structural breaks or regime shifts due to domestic and global macroeconomic and political events. The standard GARCH model does not incorporate sudden changes in the variance and hence, may be inappropriate for investigating volatility persistence and volatility forecasting. Lastrapes (1989) applies the Autoregressive Conditional Heteroskedasticity (ARCH) model to exchange rates and finds a significant reduction in the estimated volatility persistence when he accounts for monetary regime shifts. Lamoureux and Lastrapes (1990) investigate the persistence of volatility in the GARCH family of models when there are sudden changes in the variance and find that volatility persistence is overstated if structural breaks are ignored. Sudden changes in the variance can also influence the intensity or the direction of information flow among markets, stocks or portfolios as shown by Ross (1989).

Inclán and Tiao (1994) propose the Iterated Cumulative Sum of Squares (ICSS) algorithm which can help in detecting structural breaks in the volatility of a financial time series. The ICSS algorithm detects both a significant increase and decrease in volatility and, hence, can help in identifying both the beginning and the ending of volatility regimes. Wilson, Aggarwal, and Inclan (1996) apply the ARCH model on oil price futures and the associated firm portfolios and find that volatility persistence gets reduced if sudden changes in volatility are accounted for in the model. Aggarwal, Inclan, and Leal (1999) apply the ICSS algorithm on some emerging market indices for the period from 1985 to 1995, and find that volatility shifts are impacted mainly by the local macroeconomic events and the only global event over the sample period that affected several emerging markets was the October 1987 stock market crash in the United States. Malik (2003) applies the ICSS algorithm in detecting time periods of sudden changes in the volatility of five major exchange rates, and finds that volatility persistence is overstated if those sudden changes are ignored. Fernandez and Arago (2003) utilise the ICSS algorithm to detect structural changes in the variance for European stock indices and their findings are in confirmation with the findings of Aggarwal that the markets not only react to local economic and political news, but also to news originating in other markets. Malik, Ewing, and Payne (2005) find that controlling for regime shifts in volatility dramatically reduces the persistence of volatility in the Canadian stock market. Hammoudeh and Li (2008) also obtain similar findings for the Gulf Cooperation Council (GCC) stock markets. Wang and Moore (2009) find that, with the new European Union members, the persistence in volatility is significantly reduced when the model incorporates regime changes.

The central aim of this paper is to study of the impact of sudden changes in the variance on the asymmetry and persistence of volatility in the Indian stock market (specifically S&P CNX Nifty, CNX 100, S&P CNX 500, CNX Nifty Junior, CNX Midcap and CNX Smallcap) from the

vantage point of volatility modelling and to assess the forecasting ability using the GARCH class of models. The most widely used methods for detecting sudden changes in volatility are Inclán and Tiao's (1994) (IT) ICSS algorithm and the Sanso, Arago, and Carrion (2004) (AIT) ICSS algorithm. It is also a widely known fact that the financial time series exhibit fat tails. The present study compares the performance of these two methods for various data-generating processes, such as GARCH and stochastic volatility processes. In particular, earlier studies had not assessed these two methods with respect to stochastic volatility processes. In addition, we take into account leptokurtosis by making use of the Student t distribution with 5 degrees of freedom in the simulations. We then investigate empirically whether or not the inclusion of regime shifts in the GARCH class of models reduces the asymmetry and persistence of volatility in the Indian stock market. In addition, we compare the out-of-sample performance of the GARCH class of models with and without sudden changes by considering the one-step-ahead forecasting ability. We find that incorporating regime shifts in the GARCH model provides better performance in terms of forecasting ability. The study of the impact of structural changes in volatility on the accuracy of volatility forecasts has largely been ignored in the context of the Indian stock market and hence, our paper has a significant contribution to make in this area.

The remainder of this paper is organised as follows: The next section introduces the tests we will use in this study. In the third section, we undertake Monte Carlo simulation experiments to evaluate the IT and AIT ICSS algorithms. The fourth section describes the data and discusses the computational details. The fifth section reports the empirical results and the sixth section concludes with a summary of our main findings.

Methodology

Detecting points of sudden changes in variance

Inclan and Tiao's (IT) (1994) ICSS algorithm

Suppose ε_t is a time series with zero mean and with unconditional variance σ^2. Suppose the variance within each interval is given by τ_j^2, where $j = 0, 1, \ldots\ldots, N_T$ and N_T is the total number of variance changes in T observations, and $1 < k_1 < k_2 < \ldots < k_{N_T} < T$ are the change points.

$$\sigma_t^2 = \tau_0^2 \quad \text{for} \quad 1 < t < k_1 \tag{1a}$$

$$\sigma_t^2 = \tau_1^2 \quad \text{for} \quad k_1 < t < k_2 \tag{1b}$$

$$\sigma_t^2 = \tau_{N_T}^2 \quad \text{for} \quad k_{N_T} < t < T \tag{1c}$$

In order to estimate the number of changes in variance and the time point of each variance shift, a cumulative sum of squares procedure is used. The cumulative sum of the squared observations from the start of the series to the kth point in time is given as:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2$$

where $k = 1,....., T$. The D_k (IT) statistics is given as:

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, \quad k=1,...,T \quad \text{with} \quad D_0 = D_T = 0 \tag{2}$$

where C_T is the sum of squared residuals from the whole sample period.

If there are no sudden changes in the variance of the series then the D_k statistic oscillates around zero and when plotted against k, it looks like a horizontal line. On the other hand, if there are sudden variance changes in the series, then the D_k statistics values drift either above or below zero. Critical values obtained from the distribution of D_k can be used to detect the significant changes in the variance under the null hypothesis of a constant variance. The null hypothesis of constant variance is rejected if the maximum absolute value of D_k is greater than the critical value. Hence, if $\max_k \sqrt{(T/2)}|D_k|$ is more than the predetermined boundary, then k^* is taken as an estimate of the variance change point. The 95th percentile critical value for the asymptotic distribution of $\max_k \sqrt{(T/2)}|D_k|$ is 1.358 (Inclán and Tiao (1994) and Aggarwal et al. (1999)) and hence the upper and the lower boundaries can be set at ±1.358 in the D_k plot. If the value of the statistic falls outside these boundaries then a sudden change in variance is identified.

Sanso, Arago and Carrion (AIT) (2004) ICSS algorithm
Sanso et al. (2004) find certain drawbacks in the ICSS algorithm that invalidates its use for financial time series. To wit, the ICSS algorithm neglects kurtosis properties of the process and also it does not take into consideration the conditional heteroskedasticity. To circumvent these problems, they propose the AIT algorithm as a modification of IT algorithm which employs a non-parametric adjustment based on the Bartlett kernel and is given by:

$$\text{AIT} = \max_k \sqrt{T}|G_k| \tag{3}$$

where

$$G_k = \frac{1}{\sqrt{\hat{\lambda}}}\left[C_k - \left(\frac{k}{T}\right)C_T\right], \quad k=1,...,T$$

$$\hat{\lambda} = \hat{\gamma}_0 + 2\sum_{i=1}^{m}\left[1 - \frac{i}{m+1}\right]\hat{\gamma}_i$$

$$\hat{\gamma}_i = \frac{1}{T}\sum_{t=i+1}^{T}\left(\varepsilon_t^2 - \hat{\sigma}^2\right)\left(\varepsilon_{t-i}^2 - \hat{\sigma}^2\right), \quad \text{and} \quad \hat{\sigma}^2 = \frac{1}{T}C_T$$

The lag truncation parameter m is estimated using the procedure in Newey and West (1994) estimator. The 95th percentile critical value for the asymptotic distribution of AIT statistic is 1.4058.

Inclán and Tiao (1994) find that if the series has multiple change points, then it is difficult for D_k statistic to detect the correct change points in different intervals due to the masking effect. To overcome this problem of the masking effect, Inclán and Tiao (1994) propose an algorithm that looks at the different segments of the time series for the identification of change points in variance. The ICSS algorithm looks for one break point at a time by means of D_k statistic. Once the breakpoint is detected, then the sample series is further segmented to look for another break point. We also apply a similar iterative procedure for the AIT algorithm. When all the breakpoints in the series have been identified then the next step is to estimate the GARCH models with and without sudden changes in variance.

GARCH model

The log returns are calculated from the stock price indices; i.e.

$$y_t = \ln\left(\frac{P_t}{P_{t-1}}\right) * 100$$

Where P_t is a value of the index at time t and ln is the natural logarithm.

The standard generalised autoregressive conditional heteroskedasticity (GARCH) model is given as:

$$y_t = \mu + \varepsilon_t, \quad \varepsilon_t = z_t\sigma_t, \quad z_t \sim N(0,1) \tag{4}$$

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2, \tag{5}$$

Equation (5) can be rewritten as infinite-order ARCH process (assuming that $\alpha_i \geq 0$ and $\beta_i \geq 0$ for all i),

$$\phi(L)\varepsilon_t^2 = \omega + [1 - \beta(L)]\nu_t, \tag{6}$$

Where $\nu_t = \varepsilon_t^2 - \sigma_t^2$ is interpreted as an innovation for the conditional variance.

GJR-GARCH model

The GARCH model has the tendency to capture volatility clustering and it responds symmetrically irrespective of whether the news is good or bad. Engle and Ng (1993) find that a negative return shock is likely to cause more volatility than a positive return shock of the same magnitude and argue that the GARCH model underestimates the amount of volatility when responding to bad news and overestimates the amount of volatility when responding to positive news. One solution to this shortcoming in the GARCH model is provided by Glosten et al. (1993), who propose the GJR-GARCH model. The conditional variance function of a GJR-GARCH (p, q) model is given as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}\left(\alpha_i\varepsilon_{t-i}^2 + \gamma_i\varepsilon_{t-i}^2 D_{t-i}^-\right) + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2, \tag{7}$$

where D_{t-i}^- is a dummy variable and it equals 1 when ε_{t-i} is less than zero and zero otherwise.

The term $\gamma_i D_{t-i}$ allows good news ($\varepsilon_{t-i} > 0$) and bad news ($\varepsilon_{t-i} < 0$) to impact differently the conditional variance. α_i represents the impact of good news and ($\alpha_i + \gamma_i$) represents the impact of bad news on conditional volatility. Hence, if $\gamma_i > 0$, the GJR-GARCH model can capture the asymmetric property of volatility.

Combined model of sudden changes with GARCH and GJR-GARCH model

The GARCH (p, q) model with sudden changes in variance can be expressed as follows:

$$y_t = \mu + \varepsilon_t, \quad \varepsilon_t = z_t \sigma_t, \quad z_t \sim N(0,1)$$

$$\sigma_t^2 = \omega + d_1 D_1 + \ldots\ldots\ldots + d_n D_n + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2, \tag{8}$$

And the GJR-GARCH (p, q) model with sudden changes in variance can be expressed as follows:

$$\sigma_t^2 = \omega + d_1 D_1 + \ldots\ldots\ldots + d_n D_n + \sum_{i=1}^{q}\left(\alpha_i \varepsilon_{t-i}^2 + \gamma_i \varepsilon_{t-i}^2 D_{t-i}^-\right)$$

$$+ \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{9}$$

where $D_1, \ldots\ldots\ldots, D_n$ are the dummy variables taking a value of 1 from each point of sudden change in variance onwards and 0 elsewhere.

Engle and Ng (1993) propose the sign bias, negative size bias, positive size bias and joint tests in the standardised residuals to determine the response of the asymmetric volatility models to news. From Equation (4), $z_t = \varepsilon_t/\sigma_t$. Suppose S_t^- is a dummy variable which takes value 1 if ε_{t-1} is negative and S_t^+ is a dummy variable that takes value 1 if ε_{t-1} is positive and zero otherwise. Hence, the regression equations for the sign bias, negative size bias, positive size bias and joint tests are as follow:

Sign bias test: $z_t^2 = a + bS_t^- + e_t$

Negative size bias test: $z_t^2 = a + bS_t^- \varepsilon_{t-1} + e_t$

Joint test: $z_t^2 = a + bS_t^- + cS_t^- \varepsilon_{t-1} + dS_t^+ \varepsilon_{t-1} + e_t$ where a, b, c and d are constants. e_t is the residual series of the regression equations.

Monte Carlo simulation experiments

The most widely used methods for detecting sudden changes in volatility are Inclán and Tiao's (1994) (IT) ICSS algorithm and the Sanso et al. (2004) (AIT) ICSS algorithm. The comparison of IT and AIT algorithms help in assessing their relative performance in detecting sudden changes in the unconditional variance for various data-generating processes representing a variety of financial data series. In this section we undertake extensive Monte Carlo simulation experiments to study the small sample properties of the Iterated Cumulative Sum of Square (ICSS) tests which includes Inclan and Tiao's (IT) and the Sanso, Arago and Carrion's (AIT) tests and to compare their performance by means of different data-generating processes (DGP). In the first part of our analysis, we study the size properties of the IT and AIT ICSS tests. The second part analyses the power properties of the IT and AIT test. For all the data-generating processes, we have taken samples of varying sizes ($T = 100$, $T = 200$, $T = 500$ and $T = 1000$). Also, the number of Monte Carlo trials is set to 10,000 and the significance level is set at 5%.

First, we consider the data-generating processes which do not have conditional dependence and this includes the sequence of iid zero mean random numbers (the uniform distribution $U(-0.5, 0.5)$, the standard normal distribution $N(0,1)$, the standard logistic distribution, the standard exponential distribution, the Student t distribution with 5 degree of freedom and the standard lognormal distribution). Table 1 reports the rejection frequencies for both the tests for varying sample sizes.

The results indicate that the IT test suffers from a severe size distortion for all the unconditional data-generating processes except for the case of the uniform and the normal distributions. However, the AIT test exhibits desirable size properties for all the unconditional data-generating processes. The results are in confirmation with the assumptions of Inclán and Tiao (1994) which shows desirable size properties for iid Normal series.

Next, we consider the data-generating processes which take into account the conditional dependence of the series and this includes sequences from the GARCH (1,1) and the stochastic volatility (SV) processes. The following models are considered to evaluate the size properties of the tests used:

Table 1 Size properties of tests for random numbers with no conditional dependence.

	$T = 100$	$T = 200$	$T = 500$	$T = 1000$
IT				
Uniform	0.000	0.000	0.000	0.000
Normal	0.031	0.037	0.041	0.043
Logistic	0.116	0.138	0.161	0.170
Exponential	0.267	0.316	0.366	0.390
Student t	0.241	0.309	0.392	0.446
Lognormal	0.642	0.768	0.886	0.938
AIT				
Uniform	0.028	0.031	0.032	0.035
Normal	0.022	0.027	0.031	0.033
Logistic	0.018	0.022	0.027	0.031
Exponential	0.016	0.020	0.026	0.029
Student t	0.014	0.017	0.022	0.025
Lognormal	0.009	0.011	0.014	0.016

Model 1: GARCH (1,1)

$$Y_t = \sqrt{h_t}\varepsilon_t; \quad h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$$

Model 2: Stochastic volatility

$$Y_t = \exp(0.5\,h_t)\varepsilon_t; \quad h_t = \delta h_{t-1} + \varepsilon_t'; \quad \varepsilon_t' \sim N(0, 0.1)$$

In both the processes, we use two types of random errors: the standard normal distribution ($\varepsilon_t \sim N(0,1)$) and the Student t distribution with 5 degree of freedom. For the case of the standard normal distribution which is not reported here, we find desirable size properties for the GARCH (1,1) and SV processes which again confirms the underlying assumption of the IT and AIT tests. Table 2 reports the rejection frequencies of the IT and AIT tests

for the GARCH (1,1) model when the random errors are drawn from the Student t distribution.

The results shows that the IT test is severely oversized for the shocks from the Student t distribution and this is because of a violation of the assumption of normality (iid) in the case of the IT test. The results from the AIT test indicate that it is also mildly oversized for some of the cases when volatility is more persistent, but not to the extent of the IT test.

Table 3 reports the rejection frequencies of the IT and AIT tests for the stochastic volatility (SV) model when the random errors are drawn from the Student t distribution.

Again, the IT test results show a severe size distortion for all the cases. In contrast, the AIT test exhibits substantially good size properties across all parameterisations.

Table 2 Size properties of tests for the GARCH (1,1) processes.

	$\omega = 0.001$ and $\alpha = 0.1$			
β	$T = 100$	$T = 200$	$T = 500$	$T = 1000$
IT				
0.1	0.287	0.378	0.486	0.561
0.2	0.298	0.417	0.486	0.574
0.3	0.316	0.388	0.525	0.607
0.4	0.317	0.395	0.547	0.591
0.5	0.346	0.469	0.577	0.660
0.6	0.372	0.479	0.633	0.695
0.7	0.415	0.548	0.690	0.769
AIT				
0.1	0.020	0.044	0.037	0.061
0.2	0.035	0.035	0.051	0.074
0.3	0.033	0.045	0.071	0.048
0.4	0.045	0.054	0.065	0.078
0.5	0.059	0.069	0.086	0.089
0.6	0.057	0.082	0.124	0.119
0.7	0.089	0.130	0.158	0.192

Table 3 Size properties of tests for the stochastic volatility (SV) processes.

δ	$T = 100$	$T = 200$	$T = 500$	$T = 1000$
IT				
0.1	0.244	0.312	0.403	0.445
0.2	0.251	0.319	0.388	0.444
0.3	0.243	0.317	0.395	0.449
0.4	0.257	0.308	0.407	0.457
0.5	0.249	0.317	0.391	0.454
0.6	0.251	0.318	0.400	0.453
0.7	0.257	0.318	0.410	0.463
AIT				
0.1	0.014	0.018	0.020	0.024
0.2	0.015	0.017	0.022	0.024
0.3	0.014	0.017	0.020	0.025
0.4	0.016	0.018	0.023	0.026
0.5	0.014	0.018	0.019	0.026
0.6	0.015	0.019	0.024	0.023
0.7	0.015	0.019	0.023	0.025

Table 4 Power of the test when there is a change in a variance.

λ	T = 100	T = 200	T = 500	T = 1000
IT				
0.10	0.062	0.109	0.245	0.462
0.25	0.212	0.460	0.882	0.995
0.50	0.657	0.945	1.000	1.000
1.00	0.990	1.000	1.000	1.000
1.50	1.000	1.000	1.000	1.000
2.00	1.000	1.000	1.000	1.000
2.50	1.000	1.000	1.000	1.000
3.00	1.000	1.000	1.000	1.000
AIT				
0.10	0.042	0.077	0.202	0.416
0.25	0.158	0.388	0.854	0.993
0.50	0.522	0.913	1.000	1.000
1.00	0.943	1.000	1.000	1.000
1.50	0.993	1.000	1.000	1.000
2.00	0.997	1.000	1.000	1.000
2.50	0.999	1.000	1.000	1.000
3.00	0.999	1.000	1.000	1.000

Table 4 reports the power of the IT and AIT tests when there is break in the volatility of the series. We consider a sequence of iid standard Student t distribution with 5 degree of freedom for the first half of the sample and iid Student t distribution with 5 degree of freedom with the change in standard deviation by $(1 + \lambda)$ times for the second half of the series. The parameter λ indicates the percentage change in the unconditional volatility of the series.

Results show that both the tests possess desirable power properties when there is a significant break in the volatility of the series.

By means of Monte Carlo simulation experiments, we find that AIT test exhibits desirable size and power properties but that the IT test exhibits a severe size distortion for the case of fat tailed distributions. Hence, we apply the AIT test to detect sudden changes in the volatility of the Indian stock market.

Data and computational details

In order to investigate the impact of sudden changes in volatility on the volatility persistence of the Indian stock market, we have used weekly price data[2] of six indices of National Stock Exchange of India Ltd. The indices[3] used are S&P CNX Nifty (the most commonly used index, composed of 50 firms from 24 sectors), CNX100 (composed of 100 firms from 38 sectors), S&P CNX 500 (the first broad based benchmark of the Indian capital market), CNX Nifty Junior

(composed of the next 50 liquid stocks after S&P CNX Nifty), Nifty Midcap 50 (to capture the movement in the midcap segment of the market), CNX Smallcap Index (which reflects the movement in the small capitalised segment of the financial market) covering all the major segments of the Indian market. All data are obtained from www.nseindia.com. The period of study for S&P CNX Nifty is from 4-May-1994 to 27-Apr-2011 (886 observations); for CNX100 is from 1-Jan-2003 to 27-Apr-2011 (434 observations); for S&P CNX 500 is from 9-Jun-1999 to 27-Apr-2011 (620 observations); for CNX Nifty Junior is from 4-Oct-1995 to 27-Apr-2011 (812 observations); for Nifty Midcap 50 is from 3-Jan-2001 to 27-Apr-2011 (538 observations) and for CNX Smallcap Index is from 7-Jan-2004 to 27-Apr-2011 (381 observations). Each of these indices has come about at a different point in time. The choice of the sample period therefore depends on when these indices have come into existence. Furthermore, we are studying the impact of sudden changes in the variance on the asymmetry and persistence of the volatility of each individual index when considered alone and do not undertake any test across different indices. The weekly data are associated with Wednesday. If Wednesday is a holiday, Tuesday data points are used.

We have used the following abbreviations for the indices in this paper, that is Nifty for S&P CNX Nifty, CNX100 for CNX 100, CNX500 for S&P CNX 500, JUR for CNX Nifty Junior, MID for Nifty Midcap 50, SMA for CNX Smallcap index. Table 5 provides the descriptive statistics of the weekly returns for all the indices under study. The median weekly return for Nifty Midcap 50 is the highest of all the indices. The mean weekly returns of CNX 100, Nifty Midcap 50 and CNX Smallcap index are nearly the same and higher than other indices. CNX Nifty junior seems to be more volatile than the other indices. Higher weekly standard deviation for all the indices points towards a higher risk in the Indian stock market. Jarque—Bera statistics confirm the significant non-normality in the

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[2] Because daily observations may be associated with the biases due to nontrading, the bid-ask spread, asynchronous prices (Lo and MacKinlay, 1988).
[3] The indexes used in this paper use free float market capitalisation methodology.

Table 5 Descriptive statistics of stock returns.

	Nifty	CNX100	CNX500	JUR	MID	SMA
Mean	0.002	0.004	0.003	0.003	0.004	0.004
Median	0.004	0.008	0.007	0.006	0.009	0.008
Min	−0.154	−0.157	−0.168	−0.196	−0.181	−0.192
Max	0.161	0.172	0.177	0.235	0.216	0.198
Quartile 1	−0.020	−0.014	−0.013	−0.021	−0.014	−0.012
Quartile 3	0.026	0.028	0.027	0.031	0.028	0.029
St dev	0.038	0.039	0.041	0.048	0.041	0.045
Skewness	−0.120	−0.429	−0.673	−0.433	−0.622	−0.870
Kurtosis	1.369	2.406	2.354	2.712	3.417	3.245
JB-stat	72.310***	120.255***	192.358***	276.864***	300.313***	218.984***
N	886	434	620	812	538	381
ARCH-LM	58.874***	47.438***	85.743***	108.807***	40.941***	47.979***
Q(20)	33.425**	55.736***	41.298***	43.088***	57.356***	60.494***
KPSS	0.159	0.139	0.076	0.068	0.092	0.160
ADF	−8.651***	−6.635***	−7.242***	−8.223***	−6.545***	−5.407***

*** Means significant at 1% level and ** means significant at 5% level, respectively. Where ARCH-LM indicates the Lagrange multiplier test for conditional heteroskedasticity with 10 lags and JB-stat indicates the Jarque—Bera statistic.

weekly returns of all the indices. A significant negative skewness and excess kurtosis are also present in the returns of all the indices. Hence, the choice of AIT ICSS algorithm in detecting sudden changes in variance seems to be valid as the AIT ICSS algorithm exhibits desirable size and power properties for distributions with fat tails. The ARCH-LM test provides evidence in support of the presence of conditional heteroskedasticity in the returns series.

Box-Pierce Q-test strongly rejects the presence of no significant autocorrelations in the first 20 lags for all the returns series. Insignificant KPSS statistics for all indices support the non-rejection of the null hypothesis of stationarity of the series. Also the ADF test rejects the null hypothesis of a unit root in all indices returns series.

Empirical results

Sudden changes in variance

Table 6 presents the number of sudden changes in the variance, the time periods identified as when such sudden changes have occurred and the standard deviation of the returns over the respective time periods between variance changes for S&P CNX Nifty, CNX 100, S&P CNX 500, CNX Nifty Junior, CNX Midcap and CNX Smallcap indices.

We apply the AIT (modified ICSS) algorithm to identify the break points in the volatility for all the indices under study. We detect four break points in the S&P CNX Nifty index, three break points in CNX 100, five break points in S&P CNX 500, five break point in CNX Nifty Junior, three break points in CNX Midcap and two break points in CNX Smallcap which represent the presence of $(n+1)$ distinct volatility regimes in the time series of returns, where n represents the number of break points in the series. The time points of the sudden change in the volatility of indices are associated with various domestic and global economic and political events to a moderate degree. In May 2006, Indian stock market indices suffered a major decline of about 1100 points. The turbulence in the period from 2008 to 2009 was caused by the impact of the global financial crisis (sub-prime crisis) which adversely impacted the Indian stock market also. In 2009, the UPA election victory was a major event that impacted the Indian stock market in terms of reducing the uncertainty about the future of the Indian economy. These macroeconomic and political factors may have contributed to the increase in market return volatility which in turn contributed to the overall uncertainty in the Indian stock market also. In particular, we observe a higher standard deviation during the period of the sub-prime crisis for all the indices considered in this study.

Fig. 1 presents the graphical representation of the sudden changes in the variance and the related volatility regimes for all the indices under study. The bands represent ±3 standard deviations for the time point when sudden changes are experienced. Hence, the figure clearly displays where the regimes begin and end, as identified by the AIT ICSS algorithm.

GARCH (1,1) and GJR-GARCH (1,1) estimation with and without sudden changes

After identifying the time points of sudden changes in the variance of the index returns using the AIT (modified ICSS) algorithm, the next step is to introduce these sudden changes in the variance in the GARCH class of models. We apply GARCH (1,1) and GJR-GARCH (1,1) models to evaluate the impact of sudden breaks on volatility asymmetry and persistence. We set aside the last 50 observations for an evaluation of the out-of-sample performance of the GARCH class of models used in this study and the remaining observations are used for in-sample estimation.

Tables 7—12 present the parameter estimates and diagnostics obtained from the GARCH model and the GJR-GARCH model, with and without accounting for sudden changes in the volatility in the models for all the indices under study. The ARCH and GARCH coefficients (α and β) are significant at conventional level of significance for each

Table 6   Sudden changes in volatility identified by the ICSS algorithm.

Index	Number of change points	Time period	Standard deviation
S&P CNX Nifty	4	11-May-1994—18-Apr-2001	0.040
		25-Apr-2001—10-May-2006	0.028
		17-May-2006—09-Jul-2008	0.043
		16-Jul-2008—17-Jun-2009	0.065
		24-Jun-2009—27-Apr-2011	0.027
CNX 100	3	08-Jan-2003—14-Jul-2004	0.035
		21-Jul-2004—10-May-2006	0.024
		17-May-2006—17-Jun-2009	0.051
		24-Jun-2009—27-Apr-2011	0.027
S&P CNX 500	5	16-Jun-1999—18-Apr-2001	0.055
		25-Apr-2001—17-May-2006	0.030
		24-May-2006—19-Jul-2006	0.088
		26-Jul-2006—09-Jan-2008	0.031
		16-Jan-2008—17-Jun-2009	0.061
		24-Jun-2009—27-Apr-2011	0.026
CNX Nifty Junior	5	11-Oct-1995—18-Apr-2001	0.053
		25-Apr-2001—19-Apr-2006	0.035
		26-Apr-2006—19-Jul-2006	0.088
		26-Jul-2006—09-Jan-2008	0.034
		16-Jan-2008—13-May-2009	0.077
		20-May-2009—27-Apr-2011	0.030
CNX Midcap	3	10-Jan-2001—23-Jun-2004	0.038
		30-Jun-2004—10-May-2006	0.025
		17-May-2006—03-Jun-2009	0.056
		10-Jun-2009—27-Apr-2011	0.029
CNX Smallcap	2	14-Jan-2004—19-Dec-2007	0.039
		26-Dec-2007—10-Jun-2009	0.068
		17-Jun-2009—27-Apr-2011	0.032

index when sudden changes in the model are not accounted for. This indicates the time varying nature of the volatility associated with all the indices. Additionally, the volatility persistence ($\alpha + \beta$) is quite high (≥ 0.930) for S&P CNX Nifty, CNX 100 and S&P CNX 500. The persistence is between 0.930 and 0.888 for other three indices. On the other hand, when structural breaks are accounted for in the GARCH model, we find a significant reduction in volatility persistence for all the indices (0.698 for S&P CNX Nifty, 0.534 for CNX 100, 0.659 for S&P CNX 500, 0.643 for CNX Nifty Junior, 0.575 for CNX Midcap and 0.767 for CNX Smallcap). These results are consistent with the earlier findings of Lamoureux and Lastrapes (1990), Aggarwal et al. (1999), Malik et al. (2005) and others, who have argued that the standard GARCH model overestimates volatility persistence when ignoring sudden changes in the unconditional variance. Our results also support the same notion in the context of the Indian stock market that volatility persistence is significantly reduced when we explicitly incorporate regime shifts in the model.

We evaluate the accuracy of model specifications by means of several diagnostic tests. In the case of the GJR-GARCH (1, 1) model, when sudden changes in volatility are not considered, the significant value of the asymmetry coefficient (γ) implies that an unexpected negative shock is followed by greater volatility than an unexpected positive shock of the same magnitude. However, if we account sudden changes in volatility, the asymmetry coefficient (γ)

becomes insignificant at 5% level of significance for all the indices.

We find no significant serial correlations (Qs(20)) and ARCH effect (ARCH-LM (10)) in the variance equations at 5% level of significance for all the GARCH class models used in this study. However, the GARCH class of models with structural breaks provides a statistical improvement over the GARCH class of models that does not incorporate structural changes based on the highest value of log-likelihood and the lowest value of the Schwarz Bayesian Information Criteria (SIC) evaluations. In addition, we do not find any significant bias from the perspective of the sign bias, negative size bias, positive size bias and joint tests in standardised residuals, as proposed by Engle and Ng (1993), for the estimated GJR-GARCH model that incorporate structural changes for all the indices under study at 1% level of significance.

Out-of-sample forecasts

In this section, we investigate the forecasting ability of the GARCH class of models used in this study with and without incorporating sudden changes in the variance. We use the squared return as a volatility proxy for the out-of-sample evaluation. We calculate root mean squared error (RMSE), mean absolute error (MAE) and logarithmic loss errors (LL) to measure the forecast accuracy of the models used.

If $\sigma_{f,t}^2$ is a volatility forecast for day t and $\sigma_{a,t}^2$ is the actual volatility on day t, then
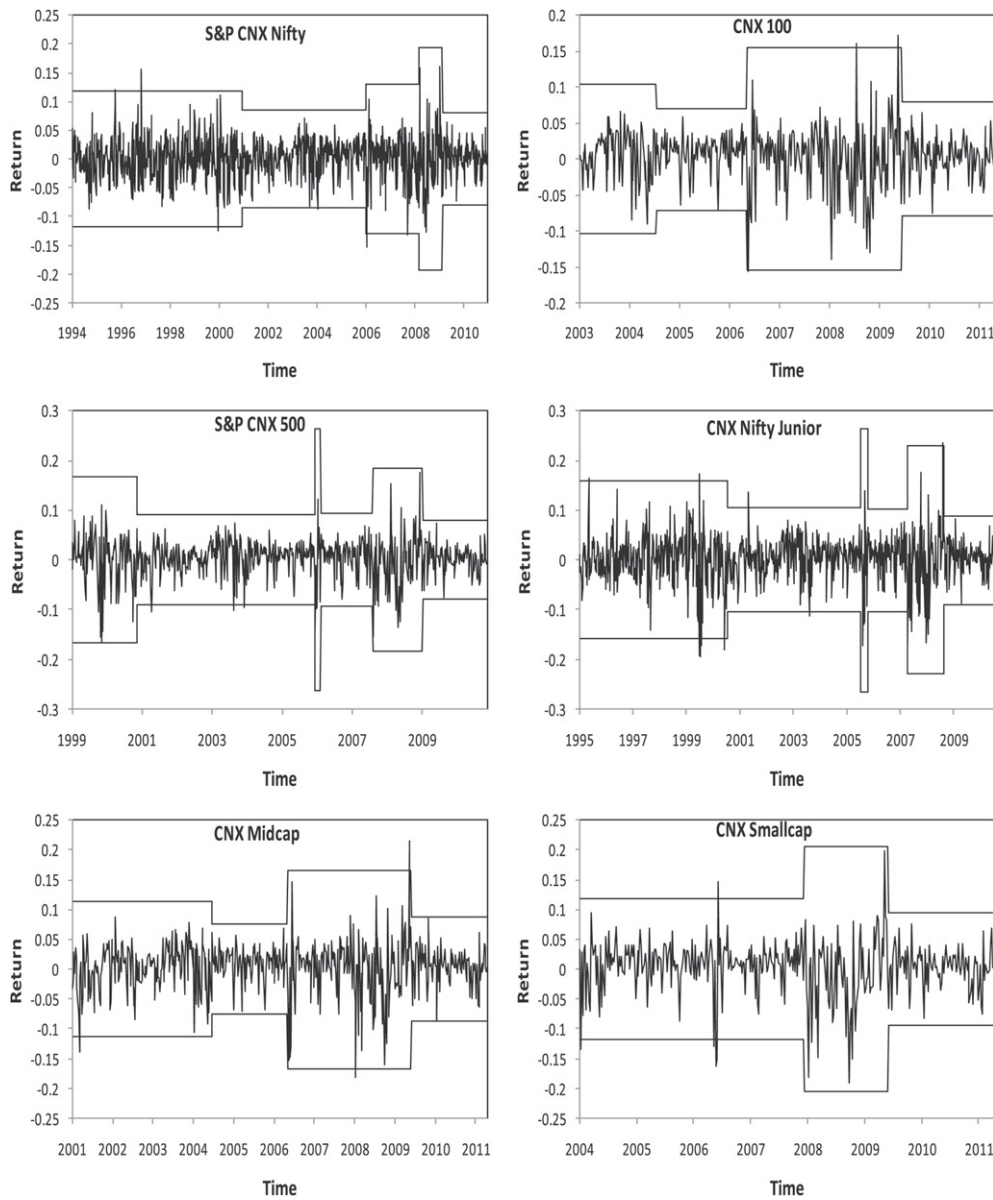
Fig. 1   Time plots for returns with band of ± 3 standard deviation for all the indices.

$$RMSE = \left[\frac{1}{T} \sum_{t=1}^{T} \left(\sigma_{f,t}^2 - \sigma_{a,t}^2 \right)^2 \right]^{1/2}$$

$$MAE = \frac{1}{T} \sum_{t=1}^{T} \left| \sigma_{f,t}^2 - \sigma_{a,t}^2 \right|$$

$$LL = \frac{1}{T} \sum_{t=1}^{T} \left[\ln \left(\frac{\sigma_{f,t}^2}{\sigma_{a,t}^2} \right) \right]$$

$$TIC = \frac{\sqrt{\frac{1}{T} \sum_{t=1}^{T} \left(\sigma_{f,t}^2 - \sigma_{a,t}^2 \right)^2}}{\sqrt{\frac{1}{T} \sum_{t=1}^{T} \sigma_{f,t}^2} + \sqrt{\frac{1}{T} \sum_{t=1}^{T} \sigma_{a,t}^2}}$$

where T is the number of forecasting data points.

Table 13 presents the forecast evaluation of 50 one-step-ahead forecasts generated from the GARCH class of models used.

The results indicate that the GARCH class of models which incorporates sudden changes in the variance provides relatively good forecasts of the Indian stock market volatility whereas the GARCH class of models without considering regime control variables seems to be a poor alternative. Hence, the results of the one-step-ahead forecast evaluation analysis suggest that the volatility models which account for sudden changes in the variance provide excellent out-of-sample predictability.

Conclusion

In this study, we compare the performance of Inclan and Tiao's (IT) (1994) and Sanso, Arago and Carrion's (AIT) (2004)

Table 7 GARCH (1,1) and GJR-GARCH (1,1) model with and without dummy variables for S&P CNX Nifty.

	GARCH (1,1)		GJR-GARCH (1,1)	
	With dummy	Without dummy	With dummy	Without dummy
μ	0.292* (0.131)	0.221† (0.125)	0.257* (0.124)	0.187 (0.121)
ω	2.492 (2.511)	1.048* (0.483)	3.100 (1.953)	1.521 (0.937)
α	0.124$^{\#}$ (0.043)	0.139$^{\#}$ (0.039)	0.025 (0.035)	0.087* (0.037)
β	0.574* (0.262)	0.793$^{\#}$ (0.058)	0.483$^{\#}$ (0.174)	0.742$^{\#}$ (0.095)
$(\alpha + \beta)$	0.698	0.932	0.508	0.829
γ			0.233 (0.395)	0.135$^{\#}$ (0.011)
Log-likelihood	−2258.729	−2271.328	−2252.682	−2268.178
SIC	5.464	5.466	5.462	5.467
JB-stat	16.878$^{\#}$	31.661$^{\#}$	12.985$^{\#}$	33.480$^{\#}$
	0.000	0.000	0.002	0.000
Q(20)	28.477†	27.026	30.167†	29.476†
	0.099	0.135	0.067	0.079
Qs(20)	12.052	7.677	15.183	8.500
	0.845	0.983	0.649	0.970
ARCH-LM(10)	0.588	0.292	1.008	0.513
	0.825	0.983	0.435	0.882
Sign bias test	2.238*	0.792	1.153	1.068
	0.025	0.428	0.249	0.285
Negative size bias test	0.212	0.827	0.928	0.392
	0.832	0.408	0.353	0.695
Positive size bias test	1.151	1.847†	0.862	1.527
	0.250	0.065	0.389	0.127
Joint test	19.390$^{\#}$	16.069$^{\#}$	4.370	8.891*
	0.000	0.001	0.224	0.031

$^{\#}$, * and † means significant at 1%, 5% and 10% level of significance, respectively.

Table 8 GARCH (1,1) and GJR-GARCH (1,1) model with and without dummy variables for CNX 100.

	GARCH (1,1)		GJR-GARCH (1,1)	
	With dummy	Without dummy	With dummy	Without dummy
μ	0.711$^{\#}$ (0.206)	0.541$^{\#}$ (0.183)	0.571$^{\#}$ (0.112)	0.525$^{\#}$ (0.170)
ω	4.152 (5.717)	1.257† (0.654)	6.349$^{\#}$ (2.295)	1.732 (1.752)
α	0.113 (0.123)	0.187* (0.079)	0.083$^{\#}$ (0.025)	0.138 (0.093)
β	0.421 (0.493)	0.746$^{\#}$ (0.088)	0.187 (0.253)	0.696$^{\#}$ (0.193)
$(\alpha + \beta)$	0.534	0.933	0.270	0.834
γ			0.252† (0.144)	0.126$^{\#}$ (0.032)
Log-likelihood	−1042.194	−1051.343	−1032.905	−1050.623
SIC	5.537	5.538	5.547	5.549
JB-stat	29.758$^{\#}$	88.016$^{\#}$	53.253$^{\#}$	87.602$^{\#}$
	0.000	0.000	0.000	0.000
Q(20)	36.288*	31.996*	32.950*	34.898*
	0.014	0.043	0.034	0.021
Qs(20)	11.303	7.333	9.846	7.574
	0.881	0.987	0.937	0.984
ARCH-LM(10)	0.686	0.438	0.580	0.507
	0.738	0.927	0.830	0.885
Sign bias test	1.171	1.078	1.242	1.432
	0.242	0.281	0.214	0.152
Negative size bias test	0.326	0.070	0.909	0.799
	0.745	0.944	0.363	0.424
Positive size bias test	1.517	1.439	1.436	1.235
	0.129	0.150	0.151	0.217
Joint test	12.533$^{\#}$	9.240*	7.860*	8.083*
	0.006	0.026	0.049	0.044

$^{\#}$, * and † means significant at 1%, 5% and 10% level of significance, respectively.

Table 9   GARCH (1,1) and GJR-GARCH (1,1) model with and without dummy variables for S&P CNX 500.

	GARCH (1,1)		GJR-GARCH (1,1)	
	With dummy	Without dummy	With dummy	Without dummy
μ	0.538# (0.149)	0.432* (0.167)	0.541# (0.146)	0.426# (0.158)
ω	3.054† (1.592)	1.200† (0.683)	4.226# (1.611)	1.577 (1.593)
α	0.161# (0.057)	0.207# (0.080)	0.081* (0.034)	0.173* (0.070)
β	0.498# (0.095)	0.738# (0.094)	0.384# (0.080)	0.700# (0.170)
$(\alpha + \beta)$	0.659	0.945	0.465	0.873
γ			0.362 (0.232)	0.092# (0.032)
Log-likelihood	−1555.248	−1577.945	−1549.677	−1577.391
SIC	5.557	5.581	5.549	5.590
JB-stat	41.357#	101.100#	39.560#	99.713#
	0.000	0.000	0.000	0.000
Q(20)	40.052#	38.059#	41.585#	40.130#
	0.005	0.009	0.003	0.005
Qs(20)	16.978	7.376	22.372	6.419
	0.525	0.987	0.216	0.994
ARCH-LM(10)	0.937	0.415	0.854	0.369
	0.499	0.940	0.577	0.960
Sign bias test	0.351	0.705	0.898	0.611
	0.726	0.481	0.369	0.541
Negative size bias test	0.343	0.059	1.064	0.374
	0.732	0.953	0.287	0.708
Positive size bias test	2.117*	1.910†	0.568	1.921†
	0.034	0.056	0.570	0.055
Joint test	8.405*	10.314*	2.453	8.310*
	0.038	0.016	0.484	0.040

#, * and † means significant at 1%, 5% and 10% level of significance, respectively.

Table 10   GARCH (1,1) and GJR-GARCH (1,1) model with and without dummy variables for CNX Nifty Junior.

	GARCH (1,1)		GJR-GARCH (1,1)	
	With dummy	Without dummy	With dummy	Without dummy
μ	0.618# (0.153)	0.512# (0.176)	0.539# (0.149)	0.468# (0.151)
ω	4.510* (2.092)	2.886* (1.273)	5.110# (1.915)	4.696* (2.326)
α	0.203# (0.056)	0.227# (0.074)	0.025 (0.049)	0.116 (0.072)
β	0.440# (0.103)	0.661# (0.112)	0.406# (0.077)	0.557# (0.157)
$(\alpha + \beta)$	0.643	0.888	0.431	0.673
γ			0.293 (0.216)	0.242# (0.079)
Log-likelihood	−2202.100	−2226.092	−2195.404	−2222.529
SIC	5.858	5.878	5.849	5.877
JB-stat	23.902#	117.830#	17.225#	194.840#
	0.000	0.000	0.000	0.000
Q(20)	39.965#	42.382#	39.038#	44.606#
	0.005	0.002	0.007	0.001
Qs(20)	18.963	13.737	19.583	10.847
	0.394	0.746	0.357	0.901
ARCH-LM(10)	0.802	0.687	0.811	0.602
	0.627	0.738	0.618	0.813
Sign bias test	1.803†	1.130	1.488	0.813
	0.071	0.258	0.137	0.416
Negative size bias test	0.582	0.046	1.247	0.637
	0.561	0.963	0.212	0.524
Positive size bias test	0.689	0.916	0.423	0.431
	0.491	0.360	0.673	0.667
Joint test	8.370*	6.645†	2.591	1.675
	0.039	0.084	0.459	0.642

#, * and † means significant at 1%, 5% and 10% level of significance, respectively.

Table 11 GARCH (1,1) and GJR-GARCH (1,1) model with and without dummy variables for CNX Midcap.

	GARCH (1,1)		GJR-GARCH (1,1)	
	With dummy	Without dummy	With dummy	Without dummy
μ	0.696# (0.182)	0.611# (0.194)	0.668# (0.167)	0.652# (0.164)
ω	4.593† (2.611)	1.730† (0.984)	6.131# (2.283)	5.683# (1.971)
α	0.113 (0.078)	0.172* (0.067)	0.037* (0.017)	0.005 (0.031)
β	0.462# (0.164)	0.741# (0.104)	0.325# (0.119)	0.442# (0.130)
$(\alpha + \beta)$	0.575	0.913	0.362	0.447
γ			0.342 (0.240)	0.417# (0.089)
Log-likelihood	−1354.149	−1364.949	−1344.137	−1359.905
SIC	5.639	5.645	5.610	5.637
JB-stat	63.735#	171.500#	52.007#	300.950#
	0.000	0.000	0.000	0.000
Q(20)	40.302#	40.036#	41.451#	45.661#
	0.005	0.005	0.003	0.001
Qs(20)	8.732	7.105	11.747	9.116
	0.966	0.989	0.860	0.957
ARCH-LM(10)	0.672	0.378	0.831	0.671
	0.751	0.956	0.599	0.752
Sign bias test	0.892	0.550	0.659	0.212
	0.372	0.582	0.510	0.832
Negative size bias test	0.396	0.314	0.827	0.494
	0.692	0.753	0.408	0.621
Positive size bias test	1.998*	1.851†	1.458	1.540
	0.046	0.064	0.145	0.123
Joint test	13.652#	9.507*	4.945	2.892
	0.003	0.023	0.176	0.409

#, * and † means significant at 1%, 5% and 10% level of significance, respectively.

Table 12 GARCH (1,1) and GJR-GARCH (1,1) model with and without dummy variables for CNX Smallcap.

	GARCH (1,1)		GJR-GARCH (1,1)	
	With dummy	Without dummy	With dummy	Without dummy
μ	0.829# (0.220)	0.756# (0.218)	0.779# (0.202)	0.732# (0.206)
ω	2.473† (1.271)	2.122# (0.797)	3.641* (1.537)	2.956 (2.392)
α	0.138* (0.056)	0.230# (0.073)	0.058 (0.044)	0.144 (0.142)
β	0.629# (0.062)	0.681# (0.071)	0.556# (0.074)	0.629# (0.178)
$(\alpha + \beta)$	0.767	0.911	0.614	0.773
γ			0.280 (0.195)	0.159# (0.049)
Log-Likelihood	−937.548	−949.273	−931.627	−948.400
SIC	5.770	5.806	5.752	5.818
JB-Stat	75.344#	97.110#	82.660#	130.410#
	0.000	0.000	0.000	0.000
Q(20)	31.261†	33.695*	32.812*	35.223*
	0.052	0.028	0.035	0.019
Qs(20)	18.556	10.589	15.609	7.662
	0.420	0.911	0.620	0.983
ARCH-LM(10)	1.588	0.918	1.443	0.625
	0.109	0.517	0.161	0.792
Sign Bias test	0.744	0.134	0.193	0.128
	0.457	0.893	0.847	0.898
Negative size bias test	0.362	0.058	0.622	0.266
	0.717	0.954	0.534	0.790
Positive size bias test	1.990*	1.475	0.729	1.185
	0.047	0.140	0.466	0.236
Joint test	4.647	3.112	1.072	1.767
	0.200	0.375	0.784	0.622

#, * and † means significant at 1%, 5% and 10% level of significance, respectively.

Table 13 Out-of-sample forecast evaluation.

	GARCH		GJR-GARCH	
	Without dummies	With dummies	Without dummies	With dummies
S&P CNX Nifty				
RMSE	11.080	8.251	11.280	8.264
MAE	10.330	7.463	10.590	7.496
LL	14.730	12.500	14.910	12.530
TIC	0.489	0.469	0.492	0.468
CNX 100				
RMSE	12.900	8.610	12.570	8.771
MAE	11.800	7.960	11.650	8.165
LL	11.430	9.009	11.370	9.023
TIC	0.514	0.469	0.510	0.467
S&P CNX 500				
RMSE	13.980	8.589	13.710	8.301
MAE	12.600	7.722	12.550	7.322
LL	15.010	11.830	14.970	11.460
TIC	0.530	0.472	0.528	0.474
CNX Nifty Junior				
RMSE	19.630	12.190	18.660	11.970
MAE	18.110	11.090	17.580	10.790
LL	14.950	11.650	14.670	11.460
TIC	0.552	0.492	0.546	0.492
CNX Midcap				
RMSE	15.140	11.630	14.600	11.850
MAE	14.150	9.818	13.820	10.230
LL	14.070	11.690	13.830	11.920
TIC	0.503	0.497	0.504	0.495
CNX Smallcap				
RMSE	18.210	14.520	17.280	14.530
MAE	16.750	11.330	15.830	11.170
LL	13.510	10.390	13.100	10.220
TIC	0.580	0.528	0.581	0.535

iterated cumulative sums of squares (ICSS) algorithms by means of Monte Carlo simulation experiments and find extreme size distortions for the IT test whereas the AIT test is correctly sized for almost all the data-generating processes considered. Hence, we apply the AIT ICSS algorithm to detect regime shifts in the Indian stock market (six major indices of Indian stock market). We also find that the regime shifts are largely associated with domestic and global macroeconomic and political events. These endogenously determined regime shifts are then incorporated in the volatility models (GARCH and GJR-GARCH models) to study the impact of shocks on volatility asymmetry and persistence. We find that the asymmetry and persistence in volatility are reduced significantly when regime shifts are accounted for in the volatility models. This suggests that ignoring sudden changes in volatility will lead to overestimating the persistence of volatility which in turn may lead to potential errors by risk managers to come up with the Value-at-Risk (VaR) measure. Also, out-of-sample forecast evaluation analysis confirms that volatility models that incorporate regime shifts provide more accurate one-step-ahead volatility forecasts than their counterparts without regime shifts. Hence, considering sudden changes in the variance may improve the accuracy of the estimation of the volatility persistence and consequently in the VaR and may help in the optimal allocation of funds.

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