Stock Market Volatility Before and After Implementation of VIX in India

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Stock market volatility has always been an area of concern for market participants and policy regulators. Through this paper, an attempt has been made to model the volatility in the Indian equity market by employing the standard GARCH(1, 1) model. The paper also investigates whether the volatility on NSE has changed after the introduction of Volatility Index (India VIX) through the GARCH(1, 1) model with a dummy. Accordingly, the period of study for measuring the volatility has been split into two, i.e., the pre-IVIX introduction period (January 1, 2000 to October 31, 2007) and the post-IVIX introduction period (November 1, 2007 to August 31, 2016). The results of GARCH(1, 1) model with a dummy reveal that the volatility of the spot market has declined after the introduction of IVIX in India. In addition, the results of standard GARCH(1, 1) models provide evidence that recent news has a greater impact on the spot market changes in the post-IVIX introduction period.

Introduction

Volatility represents the fluctuations in the returns of financial products. It is an important measure of the rate of risk of an asset. Volatility assumes great importance in foretelling the returns of a financial asset and is a vital input in pricing options and derivative products as it indicates risk in a product. Thus, understanding and predicting volatility can be of significance to market participants.

The arrival of new information in the market and the consequent dispersion in beliefs among market players will give rise to volatility. High volatility, compared to the equilibrium values of the stocks, can have significant impact on the returns of financial products. Substantial changes in the volatility of asset prices can have negative impact on risk averse investors. Its implications can also be noted on consumption patterns, corporate capital, business strategies and macroeconomic indicators. Thus, extreme volatility could affect the health of an economy by leading to major structural and regulatory changes.

Of late, the Volatility Index (VIX) introduced by the Chicago Board of Options Exchange (CBOE) has attracted a lot of attention. It is a futuristic measure of expected volatility and

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helps in the assessment of risk over a given period of time. In India, the NSE, India's premier stock exchange introduced its own volatility index (IVIX) in 2007. It was based on the methodology of the US VIX and since then it is considered a barometer of investor sentiments and market volatility.

The study of stock market volatility has always gained a lot of focus from economic research community. Many economic models have been discussed by experts to describe and predict volatility. But most of these models assume the variance of returns of the asset to be constant over a period of time. However, this assumption is rejected through empirical evidence as financial time series such as stock returns exhibit a phenomenon known as volatility clustering. This means that large changes in these series tend to be followed by large changes and small significant changes by small changes.

This behavior exhibited by stock returns or any other time series data is technically termed as Autoregressive Conditional Heteroscedasticity (ARCH) process. Accurate modeling and forecasting of the variance has assumed importance as variance is regarded as the primary measure of risk in any risk management systems. It was in 1982 that Engle for the very first time proposed the ARCH process with time-varying conditional variance. The ARCH process uses past disturbances to model the variances of the series and allow the variances of the error term to vary overtime (Karmakar, 2005). In 1986, Bollerslev further extended the ARCH process by allowing the conditional variance to be a function of past period's squared errors as well as its past conditional variance and termed it the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) process. Following the introduction of the ARCH and GARCH models, several refinements to these models have been introduced such as EGARCH, TGARCH, GJR-GARCH and so on.

The present study aims to estimate the volatility in the Indian stock market by employing the GARCH family of models. An attempt has also been made to observe the change in volatility of returns on NSE before and after implementation of the NSE Volatility Index (IVIX). Thus the time series for capturing the volatility has been split into two periods, i.e., the pre-IVIX introduction period (January 1, 2000 to October 31, 2007) and the post-IVIX introduction period (November 1, 2007 to August 31, 2016).

Literature Review

Volatility in returns is an important phenomenon observed in the stock market and there are multitudes of scholarly studies done in this area.

Poon and Granger (2001) have compared the volatility forecasting findings of 72 research papers. The study provides an insight into the issues and problems of forecast evaluation, the impact of data frequency on forecast accuracy, measuring the actual volatility, impact of extreme values on forecasting performance and providing volatility definitions. An attempt was made to compare the forecast results across asset classes and across various global markets.

Karmakar (2005) has made an attempt to capture the stock market volatility in India using the GARCH(1, 1) model. The results of the study reveal the presence of time-varying volatility with volatility clustering and high persistence and predictability of volatility. The predictive ability of fitted GARCH(1, 1) model was tested by comparing the out-of-sample volatility forecasts with true realized volatility. Looking at the 50 individual companies, it was noted that GARCH(1, 1) model successfully captures the volatility for most of the companies. Except for the four companies, a GARCH model of a higher order may have been appropriate.

Padhi (2006) has studied the stock market volatility at individual company level and also at aggregate indices level. The ARCH, GARCH and ARCH in mean model were used to examine volatility. The GARCH(1, 1) model reveals that volatility is persistent in case of individual company as well as aggregate indices. Daily data from January 1990 to November 2004 has been used in this study.

Sinha (2009) has made an attempt to model volatility on two major national indices in India. The phenomenon of volatility clustering and persistence of shock has been modeled using asymmetric GARCH models. It is observed that EGARCH model adequately captures volatility on BSE, whereas GJR-GARCH model appropriately models the conditional variance in the returns of NSE.

Joshi and Pandya (2012) have explored the volatility in the Indian and Canadian stock market. The results indicate certain conventional facts about volatility such as volatility clustering and mean reverting behavior. This is then confirmed by running the ARCH-LM test. This test shows the presence of heteroscedasticity in both the markets and the GARCH (1, 1) effectively captures the volatility in both the markets. But it is observed that the volatility in the Canadian market is slightly higher as compared to the Indian market.

Kalyanaraman (2014) has made an attempt to estimate the conditional volatility in the Saudi stock market using daily stock returns for the period from August 2004 to October 2013. The author has applied AR(1)-GARCH(1, 1) model to capture the volatility in this study. The results indicate that the Saudi stock returns are characterized by volatility clustering and follow a non-normal distribution. It also indicates persistence, predictable and time-varying volatility. The results also indicate that the past volatility of returns influence the volatility for the current period.

Waqar (2014) has estimated the volatility in the Pakistan stock market, i.e., KSE by employing various univariate GARCH family models, i.e., the GARCH(1, 1), EGARCH (1, 1) and TGARCH(1, 1). The results indicate that the GARCH(1, 1) model coefficients show that the conditional volatility on KSE is persistent and the EGARCH and TGARCH models indicate the presence of leverage effect on KSE.

Quaicoe *et al.* (2015) have attempted modeling the fluctuations in the cedi/dollar exchange rate. The various models considered are ARMA, GARCH, IGARCH, EGARCH and MGARCH. The results of the study indicate that the exchange rate series is non-stationary and it also shows the presence of ARCH effect in the series. The ARMA(1, 1) plus GARCH (1, 1) model are found to be most appropriate for modeling the variations in the cedi/dollar exchange rate in Ghana.

Eryllmaz (2015) has modeled the volatility for BIST-100 returns in the Turkish market using the ARCH, GARCH, EGARCH and TGARCH models. The results reveal that the series become stationary at first difference. Further, the ARCH-LM test is conducted to check for ARCH effect. It is concluded that the BIST-100 series could be modeled using ARCH family models. Accordingly ARCH, GARCH, EGARCH and TGARCH models are run. The author observes that the EGARCH(1, 1) model is most suitable to predict the BIST-100 return series.

Omari *et al.* (2015) have analyzed and modeled the volatility on the Ghana Stock Exchange (GSE) by examining the fluctuations for three scripts listed on GSE. The three return series are first tested for stationarity by using KPSS test and further GARCH family of models are fitted for the residual series of the three scripts. The results show the presence of volatility but no persistence is noted. The GARCH(1, 1) model is found to be appropriate for the three series.

Kulshreshtha and Mittal (2015) have analyzed and compared the volatility in the Indian stock market by analyzing eight major stock market indices, namely, BSE SENSEX, BSE-100, BSE-200, BSE-500, CNX Nifty, CNX-100, CNX-200 and CNX-500 from 2000 to 2014. Further the impact of global financial crises is also studied, and for this, the period is split into three phases: pre-crises (2000-2006), crises (2007-2010), post-crises (2011-2014). ARCH and GARCH models are used to model the volatility. It is found that the GARCH(1, 1) model is most appropriate for BSE Sensex and NSE Nifty indices for all the three periods, except for CNX Nifty index, GARCH(3, 1) is found to be suitable during post-crises period.

Quaicoe *et al.* (2015) have tested the application of different ARCH/GARCH family of models for modeling the volatility of dollar/cedi exchange rate. The variants studied include ARMA, GARCH, IGARCH, EGARCH and M-GARCH models. The results indicate the presence of ARCH effect in the series. The ARMA(1, 1) + GARCH(1, 1) model was found to be the most appropriate with all parameters significant. A 24 months ahead forecast for the series showed a depreciating trend in dollar/cedi exchange rate.

Data and Methodology

The sample comprises daily data of CNX Nifty for the period from January 1, 2000 to August 31, 2016 compiled and published by NSE India. The period of study has been split into two phases to estimate the volatility in the Indian stock market before and after the implementation of IVIX. Since IVIX was introduced by NSE in November 2007, the period from January 1, 2000 to October 31, 2007 is considered as pre-IVIX phase, whereas November 1, 2007 to August 31, 2016 is considered as post-IVIX period.

The volatility is estimated on the returns of CNX Nifty which is defined as follows:

$$R_t = \log (P_t / P_{t-1}) \quad ...(1)$$

where R_t is the logarithmic daily returns at time t and P_t and P_{t-1} are daily values of CXN Nifty at two successive days, i.e., t and $t-1$ respectively.

We further aim at fitting an appropriate GARCH model for our sample to calculate the conditional volatility. In recent times, modeling and predicting volatility with ARCH family of models has assumed excessive importance. The ARCH model given by Engle (1982) suggested that conditional variance h_t can be modeled as a function of lagged ε, i.e., predictable volatility is dependent on the past news (Karmakar, 2005). Engle gave the q^{th} order ARCH model which is defined as follows:

$$h_t = \omega + \alpha_1\varepsilon^2_{t-1} + \alpha_2\varepsilon^2_{t-2} + ... + \alpha_q\varepsilon^2_{t-q} \quad ...(2)$$

where, $\omega > 0$, $\alpha_1, \alpha_2, ..., \alpha_q \geq 0$ and $\varepsilon_t/\varepsilon_{t-1} \sim N(0, h_t)$. The ARCH($q$) model suggests that an old news which reached the market q periods ago has less impact on current market volatility. The effect of a shock on current volatility I periods ago ($I \leq q$) is thus explained by α_1. The extension to the ARCH model is the GARCH model proposed by Bollerslev (1986). In this model the conditional variance is represented as the function of its own lags and previous realized variance (Waqar, 2014). It is defined as:

$$h_t = \omega + \alpha_1\varepsilon^2_{t-1} + \alpha_2\varepsilon^2_{t-2} + ... + \alpha_q\varepsilon^2_{t-q} + \beta_1 h_{t-1} + \beta_2 h_{t-2} + ... + \beta_p h_{t-p} \quad ...(3)$$

where, $\omega > 0$, $\alpha_1, \alpha_2, ..., \alpha_q \geq 0$, $\beta_1, \beta_2, ..., \beta_p \leq 0$. The α_1 and β_1 parameters of a GARCH model indicate the short-term volatility dynamics of the resulting time series. A large β_1 coefficient indicates that the volatility is persistent, i.e., it takes long time to die out. Whereas, a large α_1 indicates the reaction of volatility to market movements is quite intense. If $\alpha_1 + \beta_1$ is close to unity, then a shock at time t will persist for many future periods. A high value $\alpha_1 + \beta_1$ implies long memory (Karmakar, 2005). The most commonly used GARCH model is the GARCH(1, 1) model which is also referred to as the vanilla GARCH or generic GARCH model.

Results and Discussion

Before developing an appropriate GARCH model for our return series to estimate volatility, we discuss the properties of the series by calculating descriptive statistics, check for stationarity using ADF and PP test and also investigate volatility clustering.

Figure 1 shows the daily closing prices of S&P CNX NIFTY index during the sample periods, viz., pre-IVIX introduction period and post-IVIX introduction period. It can be seen that the daily closing prices of S&P CNX NIFTY has upward trend during the both periods.

Besides, Figure 2 shows the daily returns of S&P CNX NIFTY index during the pre- and post-IVIX introduction period. The visual representation shows that the volatility in the returns series during the following years of post-IVIX introduction period is relatively lesser than the pre-IVIX introduction period.

Figure 1: Daily Closing Prices of S&P CNX NIFTY Index During the Sample Periods

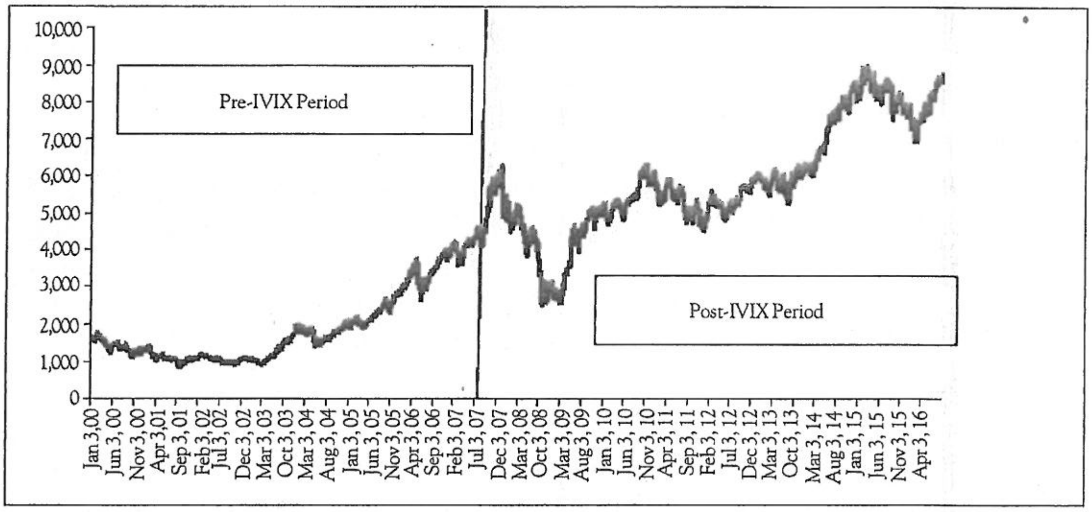
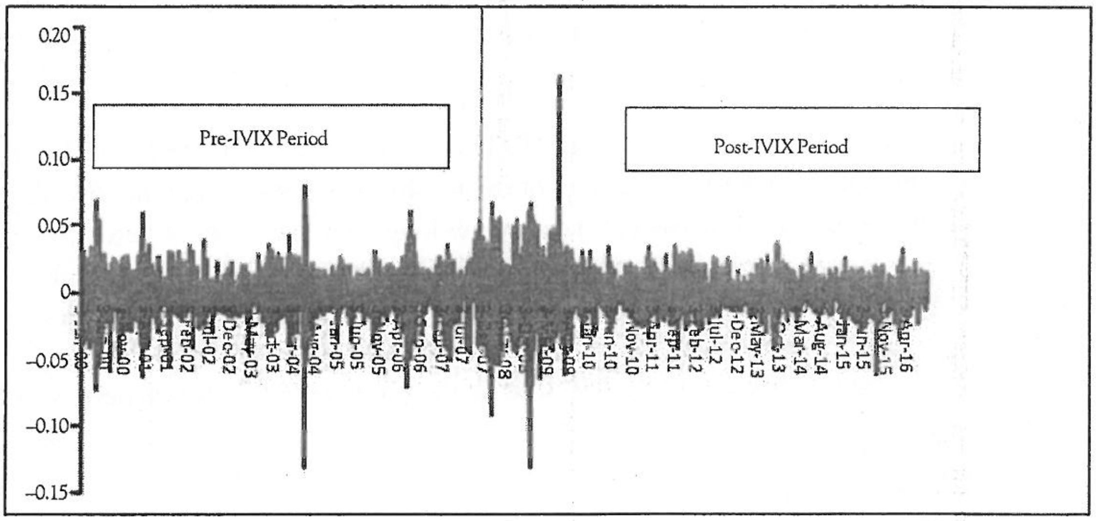


Figure 2: Daily Returns of S&P CNX NIFTY Index During the Sample Periods



In order to test the distribution of the return series, the descriptive statistics of the daily market return of S&P CNX NIFTY for the two sample periods, i.e., pre-IVIX introduction and post-IVIX introduction periods are computed and reported in Table 1. It is observed that average return of S&P CNX NIFTY is positive during the pre-IVIX introduction and post-IVIX introduction periods. The average return of NIFTY is found to be higher (0.067%) during the pre-IVIX introduction period as compared to the post-IVIX introduction (0.0185%). However, the standard deviation seems to be higher (0.015277) during the pre-IVIX introduction period. The higher value of standard deviation explains that the NSE was considered to be more volatile during the pre-IVIX introduction period.

Table 1: Descriptive Statistics of S&P CNX NIFTY Market Return		
Statistic	Pre-IVIX Introduction Period	Post-IVIX Introduction Period
Mean	0.000667	0.000185
SD	0.015277	0.015156
Skewness	–0.71256	0.083182
Kurtosis	8.158365	14.31363
Jarque-Bera Statistics	2,344.874 (0.000)	11,650.35 (0.000)

Note: Figures in the parentheses indicate *p*-values.

Statistically, the value of skewness equal to zero and kurtosis equal to 3 represents that the observed distribution is perfectly normally distributed. The results in Table 1 show that return series have non-zero skewness and the value of the kurtosis is greater than 3 in both the sample periods, implying that the returns series have a heavier tail or are leptokurtic than the standard normal distribution. The daily stock returns during the pre-IVIX introduction and post-IVIX introduction periods are, thus, not normally distributed, which is further verified by the values of Jarque-Bera statistics and its associated probability values. The Jarque-Bera statistics is used to test the normality of the data series. It examines the null hypothesis that the return series is normal against the alternative hypothesis that the return series is non-normal. From Table 1, it is confirmed that the high value of Jarque-Bera test statistics rejects the hypothesis of a normal distribution at 1% level of significance for the daily market returns of S&P CNX NIFTY during both the sample periods. Henceforth, the non-zero skewness and leptokurtic frequency distribution of return series during the pre-IVIX introduction and post-IVIX introduction periods indicate that the distribution is not normal.

Given the time series nature of the data, an initial step in the analysis is to test whether return series is stationary or not. The study employed Augmented Dickey-Fuller (ADF) test and the Phillip-Perron (PP) unit root tests for the S&P CNX NIFTY series during the pre-IVIX introduction and post-IVIX introduction periods and the results are reported in Table 2. Under ADF and PP tests, the null hypothesis of a unit root (non-stationary) is tested

Table 2: Unit Root Test Results		
Variable	ADF Test Statistics	PP Test Statistics
Pre-IVIX Introduction Period		
NSE-NIFTY Returns	–32.5153*	–40.5482*
Post-IVIX Introduction Period		
NSE-NIFTY Returns	–43.7077*	–43.6126*

Note: * indicates significance at 1% level. Optimal lag length is determined by the Akaike Information Criterion.

against the alternative of no unit root (stationary). The ADF and PP test statistics reject the null hypothesis of a unit root at 1% level of significance for both the sample periods. This indicates that the returns series examined are stationary.

To test whether there is ARCH effect in the S&P CNX NIFTY return during the pre-IVIX introduction and post-IVIX introduction periods, the ARCH-LM test (Engle, 1982) was conducted in order to test the null hypothesis of no ARCH effects on the S&P CNX NIFTY return series during the pre-IVIX introduction and post-IVIX introduction periods and the results are presented in Table 3. The ARCH-LM test statistics are highly significant at 1% level, confirming the existence of significant ARCH effects on the return data series during the pre-IVIX introduction and post-IVIX introduction periods. Figures 3 and 4 also exhibit the autocorrelation values and Q^2-statistics of S&P CNX NIFTY returns for the two sample periods, respectively. These results are also consistent with the findings of Table 3, suggesting the presence of ARCH effects in the residuals of the returns and hence the results warrant for the estimation of GARCH family models.

Table 3: ARCH-LM Test Results of S&P CNX NIFTY Market Return for the Pre- and Post-IVIX Introduction Periods

	ARCH-LM[1] Test Statistic
Pre-IVIX Introduction Period	442.319* (0.0000)
Post-IVIX Introduction Period	32.45951* (0.0000)

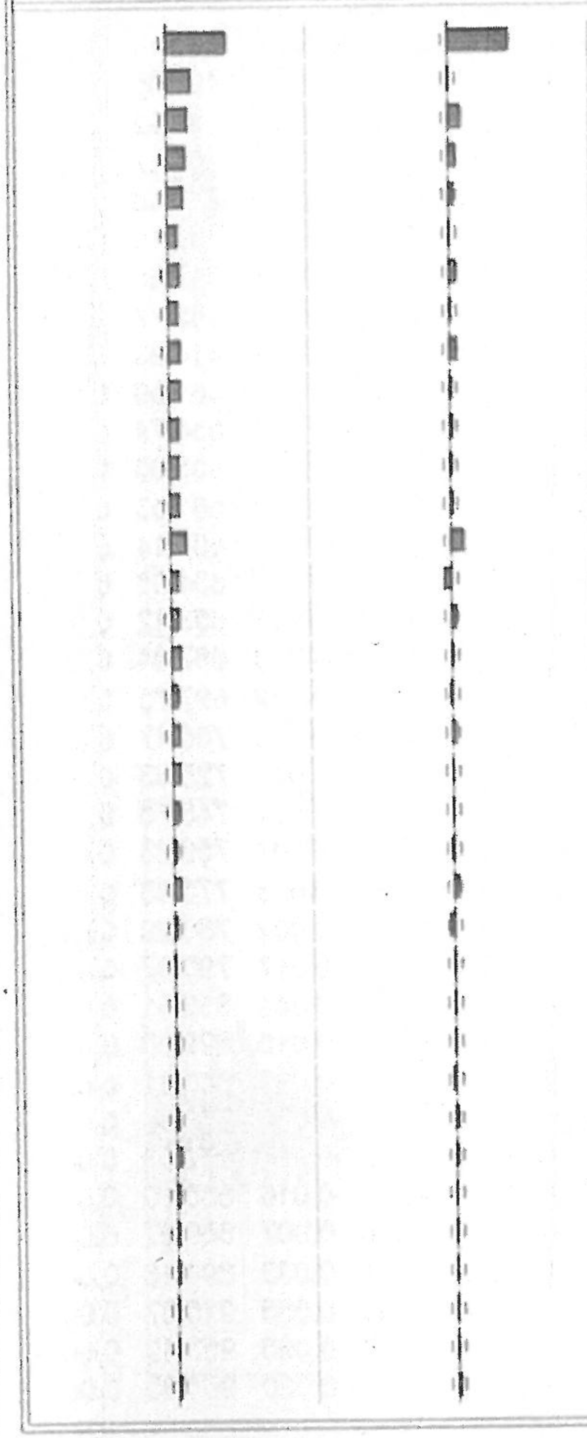
Note: * indicates significance at 1% level. ARCH-LM [1] is a Lagrange multiplier test for ARCH effects of order 1 in the residuals.

Moreover, Figures 5 and 6 exhibit the residual series of the S&P CNX NIFTY during the pre-IVIX introduction and post-IVIX introduction periods, respectively. It is observed from Figures 5 and 6 that there are stretches of time where the volatility is relatively high and relatively less, which suggests an apparent volatility clustering or ARCH effects during the pre-IVIX introduction and post-IVIX introduction periods. However, the volatility clustering in the returns series during the following years of post-IVIX introduction period is relatively less than that of the pre-IVIX introduction period.

After volatility clustering is confirmed with return series and stationarity using ADF test, heteroscedasticity effect using ARCH-LM test, we suggest that the GARCH-type models are capable and deemed fit for modeling the return volatility of Indian market, as it sufficiently captures the volatility clustering and heteroscedastic effects. Therefore, GARCH-type family models are used for modeling the volatility of return series in the Indian stock market during the pre-IVIX introduction and post-IVIX introduction periods.

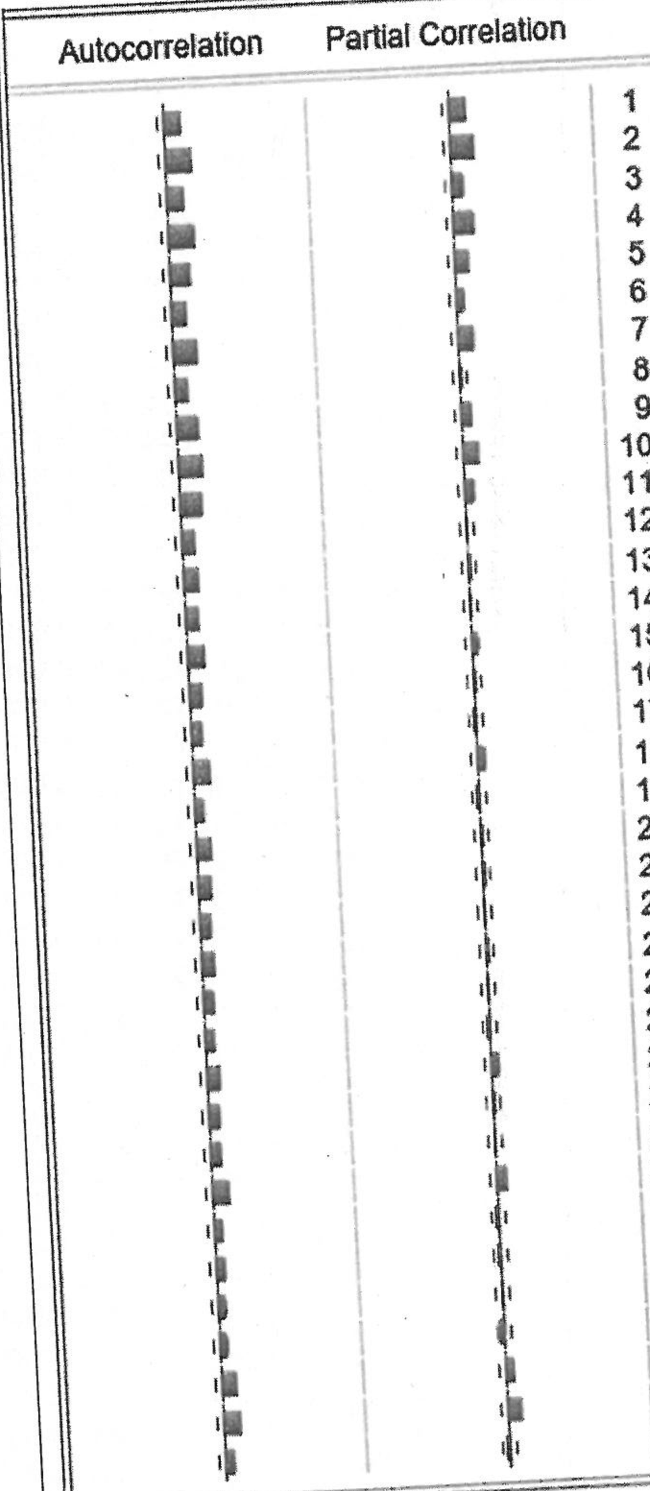
Table 4 depicts the estimates of GARCH(1, 1) model obtained to compare the volatility persistency of the Indian stock market before and after the introduction of IVIX. Comparing the parameters across the two periods, it can be seen that the estimated coefficient α_1 increases

Figure 3: Autocorrelation for the S&P CNX NIFTY Returns During the Pre-IVIX Introduction Period



	AC	PAC	Q-Stat	Prob
1	0.448	0.448	394.23	0.000
2	0.196	-0.005	470.19	0.000
3	0.159	0.092	520.27	0.000
4	0.143	0.050	560.83	0.000
5	0.120	0.034	589.29	0.000
6	0.077	-0.004	601.06	0.000
7	0.085	0.045	615.38	0.000
8	0.076	0.009	626.76	0.000
9	0.096	0.055	644.97	0.000
10	0.085	0.011	659.26	0.000
11	0.077	0.023	670.87	0.000
12	0.068	0.009	679.91	0.000
13	0.069	0.022	689.24	0.000
14	0.129	0.091	722.04	0.000
15	0.061	-0.056	729.46	0.000
16	0.061	0.039	736.84	0.000
17	0.071	0.014	746.90	0.000
18	0.047	-0.016	751.30	0.000
19	0.057	0.026	757.65	0.000
20	0.053	0.007	763.14	0.000
21	0.046	-0.002	767.27	0.000
22	0.025	-0.012	768.53	0.000
23	0.054	0.035	774.27	0.000
24	0.025	-0.033	775.56	0.000
25	0.014	-0.001	775.95	0.000
26	0.016	-0.004	776.43	0.000
27	0.017	0.003	777.01	0.000
28	0.011	-0.020	777.25	0.000
29	0.018	0.024	777.91	0.000
30	0.038	0.015	780.76	0.000
31	0.028	-0.006	782.35	0.000
32	0.021	0.006	783.26	0.000
33	0.018	-0.006	783.88	0.000
34	0.015	-0.002	784.32	0.000
35	0.008	-0.007	784.44	0.000
36	0.020	0.022	785.24	0.000

Figure 4: Autocorrelation for the S&P CNX NIFTY Returns During the Post-IVIX Introduction Period



	AC	PAC	Q-Stat	Prob
1	0.117	0.117	30.010	0.000
2	0.181	0.170	101.66	0.000
3	0.116	0.082	130.92	0.000
4	0.188	0.147	208.47	0.000
5	0.144	0.091	253.85	0.000
6	0.114	0.041	282.19	0.000
7	0.172	0.110	347.05	0.000
8	0.092	0.014	365.77	0.000
9	0.150	0.070	414.93	0.000
10	0.174	0.110	481.59	0.000
11	0.156	0.065	534.74	0.000
12	0.091	-0.004	553.00	0.000
13	0.114	0.024	581.53	0.000
14	0.094	-0.004	601.14	0.000
15	0.122	0.036	634.08	0.000
16	0.093	0.011	653.12	0.000
17	0.082	-0.010	667.84	0.000
18	0.116	0.042	697.75	0.000
19	0.063	-0.019	706.47	0.000
20	0.100	0.010	728.33	0.000
21	0.091	0.024	746.75	0.000
22	0.075	-0.007	759.23	0.000
23	0.087	0.023	775.93	0.000
24	0.068	0.002	786.29	0.000
25	0.063	-0.017	795.07	0.000
26	0.097	0.043	816.01	0.000
27	0.078	0.015	829.50	0.000
28	0.069	-0.002	840.11	0.000
29	0.117	0.068	870.34	0.000
30	0.055	-0.017	877.03	0.000
31	0.060	-0.016	885.10	0.000
32	0.046	-0.007	889.87	0.000
33	0.044	-0.033	894.18	0.000
34	0.099	0.055	915.87	0.000
35	0.130	0.095	953.49	0.000
36	0.061	-0.020	961.65	0.000

Figure 5: Volatility Clustering of S&P CNX NIFTY
During the Pre-IVIX Introduction Period

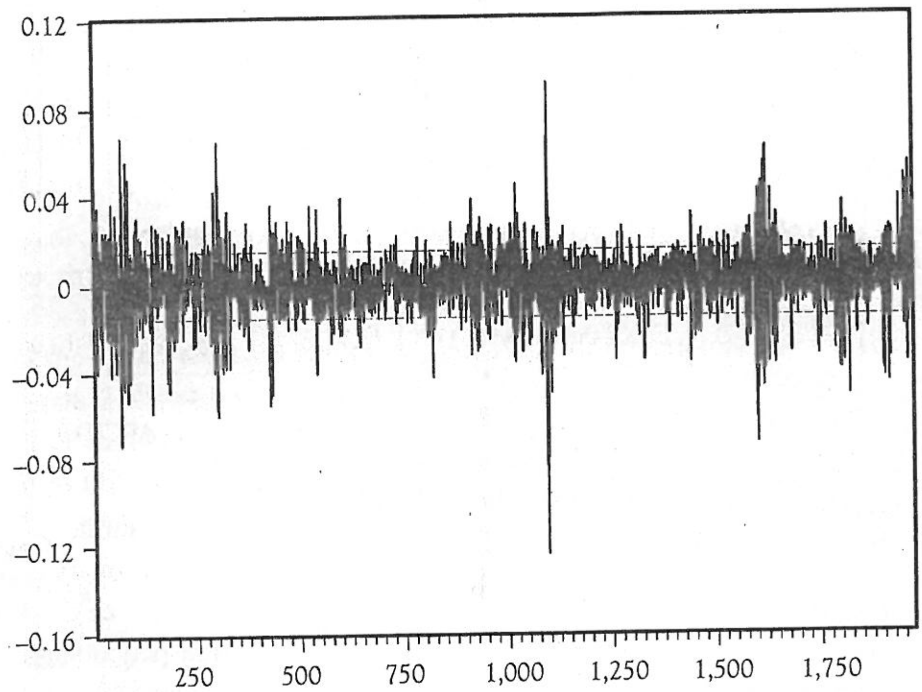


Figure 6: Volatility Clustering of S&P CNX NIFTY
During the Post-IVIX Introduction Period

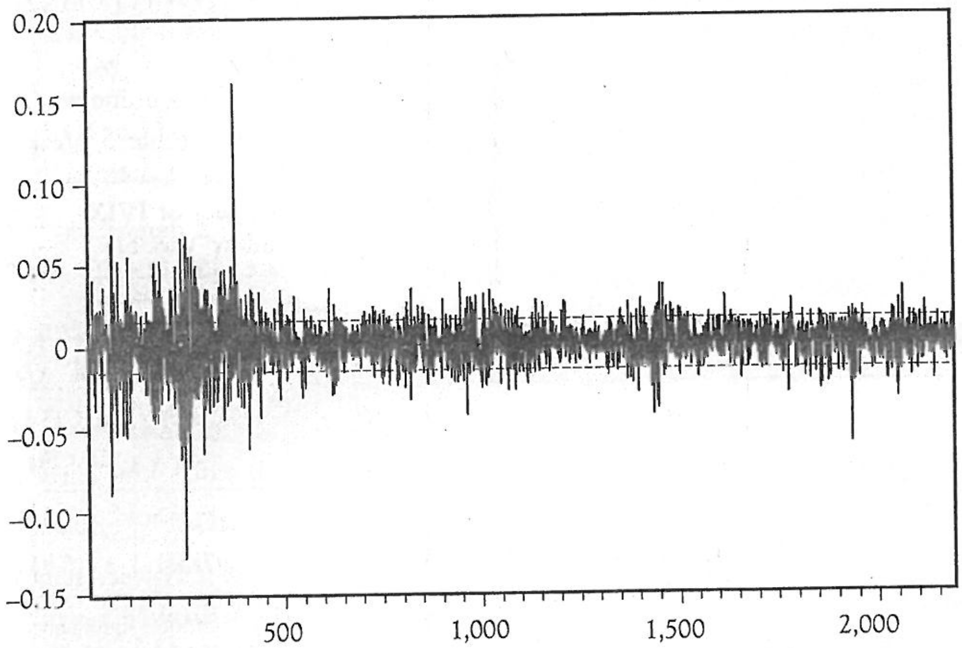


Table 4: Estimates of GARCH(1, 1) Model						
$R_t = a_0 + a_1 R_{t-1} + \varepsilon_t$ $h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1}$						
Period	a_0	a_1	α_0	α_1	β_1	ARCH-LM[1] Test Statistics
Pre-IVIX Introduction	0.001258* (4.684064)	0.101062* (4.050009)	1.18E-05* (7.857966)	0.059193* (11.13534)	0.790486* (52.74535)	0.558328 {0.455024}
Post-IVIX Introduction	0.000549** (2.368797)	0.076394* (3.202458)	1.81E-06* (4.566437)	0.078040* (9.349827	0.714453* (101.6525)	0.830603 {0.362199}

Note: Figures in ( ) and { } are Z-statistics and probability values, respectively; * and ** denote the significance at 1% and 5% level, respectively. ARCH-LM[1] is a Lagrange multiplier test for ARCH effects of order 1 in the residuals.

from 0.0591 to 0.0780 in the post-IVIX introduction period, which confirms that recent news has a greater impact on price changes. This implies that the information is being impounded more quickly following the onset of IVIX. Besides, the persistence coefficient β_1 has decreased from 0.7905 to 0.7144 in the post-IVIX introduction period suggests that increase in the rate of information flows reduce the uncertainty about previous news. In other words, following the onset of Indian VIX, the 'old news' has lesser impact in determining the volatility of the Indian spot market. This is also confirmed by the sum of coefficients α_1 and β_1. ($\alpha_1 + \beta_1$) changes from 0.9231 (pre-IVIX) to 0.7924 (post-IVIX) suggesting that persistence of shocks from the pre-IVIX introduction period to the post-IVIX introduction period is reduced.

Besides, the GARCH(1, 1) model with a dummy was employed to examine whether the introduction of IVIX stabilizes the spot market volatility in India. Table 5 presents the

Table 5: Estimates of GARCH(1, 1) Model for the Impact of IVIX on Spot Market Volatility (Whole Period) with Dummy Variable						
$R_t = a_0 + a_1 R_{t-1} + \varepsilon_t$ $h_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1} +$ DIVIX						
a_0	a_1	α_0	α_1	β_1	DIVIX	ARCH-LM [1] Test Statistics
0.000878* (4.573143)	0.0883* (5.25573)	5.64E–06* (8.718056)	0.111964* (15.91072)	0.867828* (112.47)	–1.61E–06* (–2.97183)	0.029583 {0.8634}

Note: Figures in ( ) and { } are Z-statistics and probability values, respectively; * denotes significance at 1% level. ARCH-LM[1] is a Lagrange multiplier test for ARCH effects of order 1 in the residuals.

estimates of GARCH(1, 1) model. The empirical results reveal that the IVIX dummy coefficient (DIVIX), which takes the value of 0 for the pre-IVIX introduction period (January 1, 2000 to October 31, 2007) and takes the value of 1 for the post-IVIX introduction period (November 1, 2007 to August 31, 2016), is found to be negative and statistically significant at 1% level, implying that the volatility of the spot market has declined after the introduction of IVIX in India.

Conclusion

On the whole, the empirical results of GARCH(1, 1) model with a dummy indicates that the volatility of the spot market has declined after the introduction of IVIX in India. In addition, the results of standard GARCH(1, 1) model provide evidence that recent news has a greater impact on the spot market changes in the post-IVIX introduction period. At the same time, the persistence of volatility shocks has declined in the post-IVIX scenario, indicating increased efficiency of the Indian stock market. Hence, the study suggests that the introduction of IVIX has improved the speed and quality of information flowing in the Indian stock market and has helped to curb spot market volatility in India. ❖

References

1. Bollerslev T (1986), "Generalized Autoregressive Conditional Heteroskedasticity", *Journal of Econometrics*, Vol. 31, No. 3, pp. 307-327.
2. Engle R F (1982), "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingbom Inflation", *Econometrica*, Vol. 50, No. 4, pp. 987-1008.
3. Eryllmaz F (2015), "Modelling Stock Market Volatility: The Case of BIST 100", Annals of the Constanfin Brâncusi University of Târgu Jiu, Economy Series, No. 5/2015, pp. 37-47.
4. Joshi P and Pandya K (2012), "Volatility in Stock Markets of India and Canada", *The IUP Journal of Applied Economics*, Vol. XI, No. 4, pp. 72-79.
5. Kalyanaraman L (2014), "Stock Market Volatility in Saudi Arabia: An Application of Univariate GARCH Model", *Asian Social Science*, Vol. 10, No. 10, pp. 142-152.
6. Karmakar M (2005), "Modeling Conditional Volatility of Indian Stock Market", *Vikalpa*, Vol. 30, No. 3, pp. 21-37.
7. Kulshreshtha P and Mittal A (2015), "Volatility in the Indian Financial Market Before, During and After the Global Financial Crises", *Journal of Accounting and Finance*, Vol. 15, No. 3, pp. 141-153.
8. Omari-Sasu A Y, Frempong N K, Boateng A M and Boadi K R (2015), "Modelling Stock Market Volatility Using GARCH Approach on the Ghana Stock Exchange", *International Journal of Business and Management*, Vol. 10, No. 11, pp. 169-176.

9. Padhi P (2006), "Stock Market Volatility in India: A Case of Select Scripts", *SSRN e- library*, January.

10. Poon S H and Granger C (2001), "Forecasting Financial Market Volatility: A Review", *SSRN e-library*, June 11.

11. Quaicoe M T, Twenefour F B, Baah E M and Nortey E N (2015), "Modelling Variations in Cedi/Dollar Exchange Rate in Ghana: An Autoregressive Heteroscedastic Model", *Springer Plus*, July 8, pp. 2-18.

12. Sinha B (2009), "Modelling Stock Market Volatility in Emerging Markets: Evidence from India", *SSRN e-library*, June.

13. Waqar O (2014), "Modelling Stock Market Volatility Using Univariate GARCH Models: Evidence from Pakistan", July, available at https://www.researchgate.net/publication/283486742

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