Indian Stock Market Volatility using GARCH Models: A Case Study of NSE

Bedanta Bora
Anindita Adhikary
Sikkim Manipal University
(bedanta.b@smit.smu.edu.in)
(anindita.a@smit.smu.edu.in)

DOI: 10.26573/2021.15.1.4
Volume 15, *Number* 1
January 2021, *pp.* 47-58

This paper examines volatility of Indian Stock Market returns using GARCH models that capture the volatility clustering and leverage effect. The analysed data used in the study are daily closing prices of Nifty index during 2005 to 2019. GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) models are employed after confirming unit root test, volatility clustering and ARCH effect. Asymmetric GARCH models reveal a presence of leverage effect and also confirm the effect of conditional volatility. Findings exhibit that the coefficient has a likely indication both in EGARCH (negative, significant) and TGARCH (positive, significant) models. EGARCH (1,1) model fits better to capture the asymmetric volatility.

Keywords: Nifty, Asymmetric Volatility, GARCH Models, Volatility Clustering and Leverage Effect

1. Introduction

Stock markets experience volatility that estimates the uncertainty of a security. It replicates the array to which the price of a security rises or declines. If the prices of a security change hastily and unpredictably in a given time span, it is referred to elevated volatility. If the prices of a security vary gradually, it is referred to low volatility. Financial markets are habitually anxious to the extent of asset returns which is estimated as standard deviation (Poon, 2005).

Volatility is of quite significance to investors involved in the stock markets and it portrays dispersion from a likely value. Considerable fluctuations in the share market returns result in major unfavourable effects on investors. Fluctuations may also impact consumption pattern, business investment, business cycle and macro-economic variables (Daly, 2011). The rising stock market can be interpreted as a rise in consumer spending which is directly associated with wealth effect. Rising wealth has a positive impact on consumer spending as it strengthens consumers' confidence and willingness to spend more. Conversely, declining stock market weakens the consumers' confidence leading to a fall in the consumer spending (Ludvigson and Steindel, 1999; Poterba, 2000). An increase in stock market volatility contributes to an increase in threats of equity investments, which leads to shift in business investments to less risky assets. In other words, volatility leads to a rise in the cost of funds to businesses (Zuliu, 1995). The stock market plays a vital role in macroeconomic growth and in business phases. The key theme is that higher volatility results in higher unpredictability about future economic situation. Higher uncertainty, in turn, leads to lesser expenditure and investment spending and this downfall in aggregate demand cause an economic deceleration. (Raunig and Scharler, 2010).

Arise in stock market volatility leads to a considerable fluctuation in share prices, which was evident from 1929 to 1939, in the period of America's Great Depression (Schwert, 1990). In October 1929, the price of shares declined wiping out billions of dollars of wealth indicating a Great Depression. Over the subsequent years, consumer spending and investment dropped, industrial output declined, workers lost their jobs, and thousands of banks failed.

The volatility of a market tends to be greater when a market is in a downward trend and volatility tends to be lower in an upward trend. This pragmatic experience is termed as asymmetric volatility. The explanation of asymmetric volatility may be attributed to factors such as leverage effect, distress selling, serial correlation etc (Wu.G, 2001). A decline in the share price (negative return) boosts financial leverage making the share riskier and increases its volatility (Pindyck, 1984). The occurrence of such instability is visible during the collapse of stock market when a greater downturn in share price is accompanied by a rise in volatility. The fluctuation in share prices can be observed in investors' anticipation of volatility and their hesitation to purchase a share or eagerness to sell in expectation of an unstable market.

2. Literature Review

The association of share price and its fluctuation have concerned stock market researchers. Abundant investigations have been embarked on in modelling the movements within the share market. Mandelbrot (1963) and Fama (1965) initiated the assessment on returns from stock market. Stock market returns with time series regularly show signs of volatility clustering. It refers to the observation that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes". Engle (1982) termed such movement in the sequence as Autoregressive Conditional Heteroskedasticity (ARCH). Stock market researchers further investigated the fluctuation of rising share markets by applying ARCH models. GARCH model was a generalized and extended version of ARCH technique advocated by Bollerslev (1986). Both the models were a better framework to describe the behaviour of return volatilities. GARCH (1,1) is regarded as excellent technique to capture conditional volatility from a wide range of financial data (Matei 2009). GARCH (1,1) technique has also been successful in predicting the instability in US share market as compared to other techniques (Akgiray, 1989).

Although, the ARCH and the GARCH techniques have been considered as better in capturing the fluctuation of the fiscal time sequence information, they have been unsuccessful in assessing the leverage effect where the conditional variance is likely to react asymmetrically to affirmative and pessimistic market information. Stocks react harshly during the market downturn, showing volatility asymmetry (Bekaert and Wu, 2000). The emerging nations exhibit greater asymmetric volatility at the time of financial instability (Jayasuriya and Rossiter, 2008). Several expansions of GARCH techniques have been put forward to apprehend the leverage effect. An exponential GARCH (EGARCH) technique based on logarithm of the conditional volatility in the financial time series information was applied for further assessing the stock market volatility (Nelson 1991). Thereafter, a number of amendments were put forward. Amongst them, is the establishment of Threshold ARCH (TGARCH) model for studying the effect of affirmative and pessimistic information (Zakoian 1994). Further research works reflect that the EGARCH and TGARCH techniques attained better results in anticipating the stock market information (Chen and Lian, 2005).

A few research initiatives have been carried out on fluctuations in share market returns in emerging nations. The volatility was examined in the stock market in India and investigated the existence of fluctuation during 1990s (Roy and Karmakar, 1995). A study of Indian market has also revealed the presence of asymmetric volatility (Goudarzi and Ramanarayanan, 2011). Unexpected shocks cause asymmetric volatility and positive news lead to favourable results than adverse news (Entorf and Darmstadt, 2007). The existence of asymmetry was revealed in the returns of Indian market through the application of TGARCH(1,1) model as well. The research work to predict the fluctuations in Indian stock market was undertaken by comparing the results of unconditional and conditional volatility techniques (Ajay, 2005). GARCH technique was applied in assessing the co-movement and volatility transmission in Indian and US share market (Kumar and Mukhopadhyay, 2002). The effect of introducing index options and futures on fluctuations in stock index was examined by the application of GARCH technique (Shenbagaraman, 2003). The volatility in the daily return of NSE was assessed using GARCH model where this model proved to predict the fluctuations better compared to other techniques (Banerjee and Sarkar, 2006). The volatility was examined by considering the daily information from stock indices of Middle East namely the Egyptian CMA index and the Israeli TASE-100 index. The study applied the GARCH class of model and revealed that the coefficient of EGARCH model depicted a negative and significant value for both indices. The study further indicated the presence of the leverage effect (Floros, 2008). Time-varying volatility forecasting exercise was carried out for the National Stock Exchange. Both symmetric and asymmetric GARCH models advocated that the volatility of the National Stock Exchange returns was persistent and asymmetric in nature, which was the outcome of the crisis (Tripathy and Gil-Alana, 2015). The volatility of the Indian stock market was examined considering the time series data of daily closing prices of S&P CNX Nifty Index from 2003 to 2012. The investigation was carried out applying both symmetric and asymmetric GARCH models. The study confirmed the presence of asymmetric effect as depicted by EGARCH (1,1) and TGARCH (1,1) models and further proved that unfavourable news has considerable effect on volatility (Banumathy and Azhagaiah, 2015). The study intended to assess the volatility of Indian equity market from 2003 to 2015 by the application of the GARCH family models. The study confirmed the presence of volatility that revealed the clustering and persistence of stocks. The study further proved that the good and bad information responded asymmetrically. The unfavourable news reported more volatility than the unfavourable news of the same magnitude for the selected stocks (Amudha and Muthukamu, 2018). The volatility and leverage effect of four emerging share markets namely Brazil, India, Indonesia and Pakistan were examined. The research work considered the returns of 5 years from 2014 to 2018. The investigation was carried out by the use of GARCH family model and the leverage effect was examined by EGARCH model. The result provided the evidence of presence of volatility clustering and leverage effect where the favourable news affected the stock market than unfavourable news (Kumar and Biswal, 2019).

Most of the studies attempted on modelling volatility have been applied on stock market data from developed countries. Even though, a few research studies have been focused on Indian market, the study for long period of 15 years using ARCH and GARCH methods is scanty. As such, the authors are motivated to make an effort to estimate volatility clustering and leverage effect in India stock market.

3. Objectives of the Study

The objectives of the present study are:

1. To estimate the existence of volatility in India stock market by applying the GARCH family of models.
2. To investigate the presence of volatility clustering and leverage effect by applying asymmetric models.

4. Research Methodology

4.1 Data Source

The current research work is based on S&P CNX Nifty index value acquired from the website of National Stock Exchange (NSE). The data embodied in the study are Nifty index's daily closing prices. The data spans from April 2005 to March 2019. The year from 2005 to 2019 presents an economy where there has been a blended experience of global financial crisis and boom in Indian economy that affected the stock market. The study considers closing values on everyday basis. S&P CNX Nifty index is considered as a representative sample of share value in India as it is believed to reflect the performance of the entire stock market.

4.2 Investigation Tools

Augmented Dickey Fuller (ADF) test, Philips-Perron (PP) test, Autoregressive Conditional Heteroscedasticity - Lagrange Multiplier (ARCH-LM) tests and GARCH family of models were applied for the present research. The study has employed E-views 10 package for the purpose of investigation.

Volatility is estimated on daily index returns. The difference in the logarithm of Nifty index value for the two following days is first calculated so that data covering a large range of values are converted to a more manageable size.

4.3 Elementary Measurements of Nifty Index Return

4.3.1 Descriptive Calculation

To categorise the distributional nature of the daily Nifty index return sequence, the descriptive tools like mean, median, skewness, kurtosis and Jarque-Bera statistics tools are applied.

4.3.2 Stationary Test

To examine the stationarity of the index return time sequence, unit root test has been carried out. A time series of index return is believed to be stationary only when both mean and variance are steady eventually. But a time series which is non-stationary and with an existence of unit root will have a changing mean or variance or both. Here, the test of stationarity is performed by ADF test (Dickey and Fuller, 1979) and PP test (Phillips and Perron, 1988).

The outcome of a time series that is not static can be calculated for the precise occasion only and assessment cannot be universal. So, a series must be stationary. Moreover, a non-static time sequence cannot give pragmatic results for prediction purpose. As Nifty index return happens to be a time series variable, it must be static in character otherwise movements cannot be predicted. Hence, the index returns information used in this paper requires examination to confirm the existence of unit root by using the Augmented Dickey Fuller test.

Null hypothesis : H_0 : There is a unit root; the time series is non-stationary.
Alternate hypothesis : H_a : There is no unit root; the time series is stationary.

4.3.3 Heteroscedasticity Test

It is extremely vital to first examine the residuals for the existence of heteroscedasticity before applying the GARCH model. In statistics, heteroscedasticity occurs when the standard error of a variable, monitored over a specific period of time, is not a constant. The existence of heteroscedasticity is important in analysis of variance as it nullifies statistical tests of significance that assume that all modelling errors have the same variance. The presence of heteroscedasticity in residual of the return is confirmed by applying the Lagrange Multiplier (LM) test. The LM test is a principle for assessing hypotheses about factors in a likelihood structure.

4.3.4 Tools for measuring Volatility

The Generalized ARCH (GARCH) methodology that is symmetrical in nature will not be suitable to evaluate the unsteadiness in time series. To capture the asymmetrical data, Exponential GARCH (EGARCH) methodology advocated by Nelson (1991) and Threshold GARCH (TGARCH) advocated by Glosten, Jaganathan and Runkle (1993) and Zakonian (1994) are applied. However, there is no single model that can be named "best" as extensions of GARCH are suited for different cases.

4.3.4.1 GARCH (1, 1)

The GARCH model in which the conditional variance rest on the former lags; specifies the conditional variance equation as:

mean equation : $r_t = \mu + \varepsilon_t$ and

variance equation: $\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$,

where r_t is the return of the asset at time t, μ is the average return and ε_t is the residual return and where $\omega>0$, $\alpha \geq 0$, $\beta \geq 0$. The degree of factor α and β denote the variability in time series. If $(\alpha + \beta)$ is close to unity, it states that a distress at time t will carry on for future period.

4.3.4.2 EGARCH (1, 1)

The volatility that happens to decline when return rises and that happens to rise when the return falls are often called the leverage effect (Enders 2004). EGARCH method captures asymmetric reaction of the time changing variance where variance is constantly affirmative. EGARCH (1, 1) is defined as,

$$\log(\sigma^2_t) = \omega + \beta_1 \log(\sigma^2_{t-1}) + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma^2_{t-1}} \right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma^2_{t-1}}$$

$\log(\sigma^2_t)$ denotes the log of the conditional variance. The coefficient γ signifies the asymmetry or leverage factor. The existence of leverage effects can be examined by the hypothesis that $\gamma<0$. The shock is symmetric if $\gamma \neq 0$.

4.3.4.3 TGARCH (1, 1)

The equation of the TGARCH for the conditional variance is:

$$\sigma^2_t = \omega + \alpha\, \varepsilon^2_{t-1} + \gamma\, d_{t-1}\, \varepsilon^2_{t-1} + \beta\sigma^2_{t-1},$$

where γ is termed as the asymmetry or leverage factor. Here, positive facts ($\varepsilon_{t-1} > 0$) and the adverse data ($\varepsilon_{t-1} < 0$) have variance outcome. Thus, where γ is substantial and positive, negative information has more consequence on σ^2_t as compared to the positive information.

5. Empirical Results

Table 1 shows descriptive analysis of Nifty index returns during the study period. As reflected in the Table, mean returns of Nifty are 0.000216 and a standard deviation of 0.000347. The returns mean is positive which portrays that there is a rise in the share price during that period. Skewness of the distributions of Nifty returns is negative. Negative skewness connotes a higher chance of generating returns that is greater than mean. Kurtosis of the distributions of Nifty index returns is leptokurtic (>3) depicting fat tail in the return sequence with a normal distribution. It is further confirmed by Jarque-Bera test that is significant at 1% level. Thus, the null hypothesis of normality is rejected.

Table 1 *Descriptive Statistics of S&P CNX Nifty Returns*

Particulars	Nifty Returns
Mean	0.000216
Median	0.000347
Maximum	0.070939
Minimum	-0.056520
Std. Dev.	0.006075
Skewness	-0.053416
Kurtosis	13.74739
Jarque-Bera	16697.12
Probability	0.00000
Sum	0.749875
Sum Sq. Dev.	0.128005
Observation	3469

Figure 1 portrays volatility clustering of S&P CNX Nifty return from April 2005 to March 2019. It can be noted that the stage of low volatility has a tendency to be followed by the stage of low volatility for a longer period and the stage of elevated volatility is followed by the stage of elevated volatility for a longer period. This specifies that the volatility is clustering and the Nifty index return series change about the constant mean but the variance is changing with time.

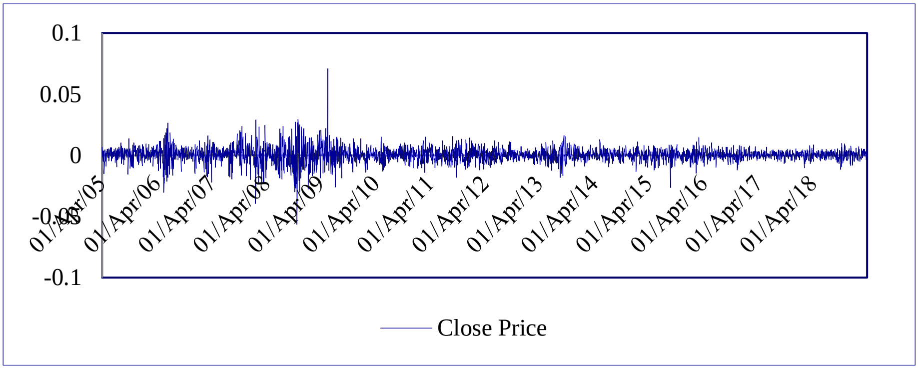

Figure 1 *Volatility Clustering of Daily Return of S&P CNX Nifty*

The test for stationarity is carried out by ADF test and PP test. Table 2 presents the result of unit root test of index return series using ADF and PP tests. The p values of ADF and PP are less than 0.05 which specify that the index return series during the research period are stationary. ADF test and PP test reject the null hypothesis that there is a presence of a unit root in the index return series in all three levels of significance. Hence, the result of ADF test and PP tests statistics validate that the series is stationary.

Table 2 *Unit Root Test*

Value	ADF	PP
t-statistics	-55.43342	-55.41358
Prob.	0.0001	0.0001
Critical Value		
1%	-3.432048	-3.432048
5%	-2.862176	-2.862176
10%	-2.567152	-2.567152

The estimated result of ARCH-LM test is shown in Table 3. The ARCH-LM test is used to assess the existence of arch effect in the residuals of the return series. Since $p > 0.05$, the null hypothesis of 'no arch effect' is accepted. This concludes that the test statistics do not support for any further arch effect remaining in the residuals of the models.

Table 3 *Estimated Result of ARCH-LM Test*

	ARCH-LM test for heteroscedasticity		
F-Statistics	0.431178	Prob. F (1,2969)	0.5126
Obs *R-squared	0.431425	Prob. Chi-Square (1)	0.5122

Table 4 represents the estimated outcome of GARCH (1,1) model. It reflects that the factor of GARCH is noteworthy. In the mean equation, constant value is positive and significant as $p<0.05$. The coefficients on both the lagged squared residual (ARCH) and lagged conditional variance (GARCH) in variance equation are highly significant. In the conditional variance equation, the β coefficient is noticeably high as compared to α coefficient. This infers that the share market has a memory extended to more than one era. At the same time, the volatility is more responsive to its lagged values compared to the recent shocks in the market reflecting that the volatility is persistent. The sum of the coefficients (α and β) is 0.9942, which is close to unity signifying that volatility is quite recurring in nature. Thus, the GARCH model proved that conditional variance is repeated in the Indian stock market. The AIC and SC criteria of the model are -7.650418 and -7.642357 respectively.

Table 4 *Estimated Result of GARCH (1,1) Models*

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4))*GARCH(-1)				
Variance	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C (μ)	0.000351	$8.02e^{-5}$	4.336969	0.0000
Variance Equation				
C (ω)	$3.27e^{-7}$	$5.99e^{-8}$	5.459731	0.0000
RESID (-1) ^2 (α)	0.087521	0.006619	13.22159	0.0000
GARCH(-1) (β)	0.906711	0.006686	135.6102	0.0000
α + β	0.994232			
Akaike info. Criterion	-7.650418	Schwarz Criterion	-7.642357	

The volatility through EGARCH (1, 1) methodology is observed to consider the effect of favourable and adverse statistical data. The outcome of EGARCH (1, 1) model is shown in Table 5. The outcome reveals the occurrence of leverage effect. C (4) is negative i.e. -0.079592 and statistically significant which specifies that any change in price responds asymmetrically to the favourable and adverse information in the market. Further, it can be concluded that affirmative news create less variance or volatility than bad news. Hence, unfavourable information plays a very important part in volatility in comparison to affirmative news. The AIC and SC criteria of the model are -7.667898 and -7.657812 respectively.

Table 5 *Estimated Result of EGARCH Model*

LOG(GARCH)=C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1)))+ C(4)*RESID(-1)/@SQRT(GARCH(-1))+C(5)*LOG(GARCH(-1))				
Variance	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C(μ)	0.000219	$7.8e^{-5}$	2.760954	0.0062
Variance Equation				
C(2)(ω)	-0.335728	0.030573	-10.98363	0.0000
C(3)(α)	0.186781	0.011218	16.66170	0.0000
C(4)(β)	-0.079592	0.007012	-11.36654	0.0000
C(5) (γ)	0.981511	0.002398	410.6656	0.0000
Akaike info. Criterion		-7.667898	Schwarz Criterion	-7.657812

The leverage effect is measured through TGARCH (1, 1) model and the outcome of the model is shown in Table 6. The C(4)*(RESID(-1)^2*(RESID(-1)<0) is positive and statistically significant. This supports the statement that leverage effect exists in the model and unfavourable information has greater effect on conditional variance than the favourable information. The AIC and SC criteria of the model are -7.665572 and -7.655483 respectively.

Table 6 *Estimated Result of TGARCH Model*

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4))*RESID(-1)^2*(RESID(-1)<0) + C(5)*GARCH(-1)				
Variance	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.000242	$8.18e^{-5}$	2.829389	0.0047
Variance Equation				
C	$4.27e^{-7}$	$6.03e^{-8}$	7.077394	0.0000
RESID(-1)^2	0.038461	0.005812	6.625198	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.100238	0.010519	9.533296	0.0000
GARCH(-1)	0.901678	0.006723	134.2142	0.0000
Akaike info. Criterion		-7.665572	Schwarz Criterion	-7.655483

The best fitted model in the GARCH family of models is chosen based on the lowest AIC and SIC value. The AIC and SIC values (-7.667898 and -7.657812) of EGARCH model is the lowest. Therefore EGARCH (1,1) model appears to be a satisfactory explanation of volatility.

6. Conclusion

This research work examines the volatility of S&P CNX Nifty index returns. The daily closing prices of the index are gathered for fifteen years from 2005 to 2019 and examined applying GARCH methods. The methods captured the volatility clustering and leverage effect during the study period. The test of unit root, volatility clustering and ARCH effect are confirmed and established. The Nifty index returns are further analysed by GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) models. In GARCH (1,1) model, α coefficient and β coefficient are highly significant and the β coefficient is noticeably high compared to α coefficient which concludes that the share market has a memory extended to more than one period. Further, the sum of the coefficient of α and β is 0.9942, which reflects that the volatility is quite recurring in nature. EGARCH (1,1) model reveals the existence of leverage effect which specifies any change in price responds asymmetrically to the favourable and adverse information in the market. The leverage effect measured through TGARCH (1,1) model is positive and statistically significant concluding the existence of leverage effect throughout the study period. Finally, to select the best fitted model amongst the GARCH models, AIC and SIC are applied and EGARCH (1,1) model is proved to be the finest model to apprehend the share market volatility. The overall conclusion of this research work supports the results of earlier studies conducted by Floros (2008), Banumathy & Azhagaiah (2015) and Kumar and Biswal (2019).

7. Limitations and Scope for Future Research

This paper examines volatility of Indian Stock Market returns using GARCH models that captures the volatility clustering and leverage effect. The present work suffers from the limitation of use of only three classes of GARCH model namely GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) models. The study has also considered only one Index for capturing the existence of volatility in India stock market. Henceforth, other GARCH family of models can be applied to the present work for better assessment. In addition to these, the analysis may suitably be extended towards other indices of India and select developed nations.

8. References

1. Ajay, P., ‘Modeling and Forecasting Volatility in Indian Capital Markets’, *Vikalpa*, 30, 2005, 27-46.
2. Akgiray, V., ‘Conditional Heteroscedasticity in Time Series of Stock Returns: Evidence and Forecast’, *Journal of Business*, 62(1), 1989, 55-80.
3. Amudha, R. & Muthukamu, M., ‘Modeling Symmetric and Asymmetric Volatility in the Indian Stock Market’, *Indian Journal of Finance*, 12(11), 2018, 23–36.
4. Banerjee, A. & Sarkar, S., ‘Modeling daily Volatility of the Indian Stock Market using intra-day data, Working Paper Series’, WPS No. 588/. http://financelab.iimcal.ac.in/resdoc/WPS-588.pdf, 2006.
5. Bekaert, G. & Wu, G., ‘Asymmetric volatility and risk in equity markets’, *Review of Financial Studies*, 13(1), 2000, 1–42.
6. Bollerslev, T., ‘Generalized Autoregressive Conditional Heteroskedasticity’, *Journal of Econometrics*, 31(3), 1986, 307-327.
7. Raunig, B. & Scharler, J., ‘Stock Market Volatility and the Business Cycle’, *Monetary Policy & The Economy*, Q2/10, 2010, 54-63
8. Chen, W. Y. & Lian, K. K.,‘A Comparison of Forecasting Models for ASEAN Equity Markets’, *Sunway Academic Journal*, 2, 2005, 1-12.
9. Daly, K., ‘An Overview of the Determinants of Financial Volatility: An Explanation of Measuring Techniques’, *Modern Applied Science*, 5(5), 2011, 46-63.
10. Dickey, D. A. & Fuller, W. A., ‘Distribution of the Estimators for Autoregressive Time Series with a Unit Root’, *Journal of American Statistical Association*, 74(366), 1979, 427–31.
11. Enders, W., ‘Applied Econometric Time Series, by Walter’, *Technometrics*, 46(2), 2004.
12. Engle, R. F., ‘Autoregressive Conditional Heteroscedasticity with Estimates of Variance of United Kingdom Inflation’, *Econometrica*, 50(4), 1982, 987–1008.
13. Entorf, V. H., & Darmstadt, C. S., ‘Announcement of Business Cycle Forecasts and the reaction of the German Stock Market’, *Year books of Economics and Statistics*, Lucius & Lucius, Stuttgart Publisher, 227(1), 2007, 1-26.
14. Fama, E., ‘The Behaviour of Stock Market Prices’, *Journal of Business*, 38(1), 1965, 34-105.

15. Floros, C., ‘Modelling Volatility using GARCH Models: Evidence from Egypt and Israel.’, *Middle Eastern Finance and Economics*, 2, 2008, 31–41.
16. Glosten, L. R., Jagannathan, R. & Rukle, D. E., ‘On the relation between the expected value and volatility of the nominal excess return on stocks’, *Journal of Finance*, 48, 1993, 1779-1801.
17. Goudarzi, H. & Ramanarayanan, C. S., ‘Modeling Asymmetric Volatility in the Indian Stock Market’, *International Journal of Business and Management*, 6(3), 2011, 221-230.
18. Jayasuriya, S. A. & Rossiter, R., ‘Asymmetric Volatility in Asian Equity Markets’, *Journal of International Finance and Economics*, 8(4), 2008, 11-21.
19. Banumathy, K. & Azhagaiah, R., ‘Modelling Stock Market Volatility: Evidence from India’, *Managing Global Transitions*, 13(1), 2015, 27-41.
20. Kumar, A. & Biswal, S. K., ‘Impulsive Clustering and Leverage Effect of Emerging Stock Market with special reference to Brazil, India, Indonesia, and Pakistan’, *Journal of Advanced Research in Dynamical and Control Systems*, 2019, 11, 33–37.
21. Kumar, K. K. & Mukhopadhyay, C., ‘A Case of US and India’, Paper published as part of the NSE Research Initiative available at www.nseindia.com, 2002.
22. Ludvigson, S. & C. Steindel, ‘How Important is the Stock Market Effect on Consumption’, *Federal Reserve Bank of New York Economic Policy Review*, 5(1), 1999, 29-51.
23. Mandelbrot, B., ‘The Variation of Certain Speculative Prices’, *Journal of Business*, 36(4), 1963, 394-419.
24. Matei, M., ‘Assessing Volatility Forecasting Models: Why GARCH Models take the lead’, *Romanian Journal of Economic Forecasting*, 4, 2009, 42-65.
25. Nelson, D., ‘Conditional Heteoskedasticity in Asset Returns: A New Approach’, *Econometrica*, 59(2), 1991, 347-370.
26. Phillips, P. C. B. & Perron P., ‘Testing for a Unit Root in Time Series Regression’, *Biometrika*, 75(2), 1988, 335–46.
27. Pindyck, R. S., ‘Risk, Inflation, and the Stock Market’, *The American Economic Review*, 74(3), 1984, 335-351.
28. Poon, S. H., ‘A Practical Guide to Forecasting Financial Market Volatility, West Sussex’, *John Wiley and Sons*, 2005.
29. Poterba, J. M., ‘Stock Market Wealth and Consumption’, *Journal of Economic Perspectives*, 14(2), 2000, 99-118.
30. Roy, M. K., & Karmakar, M., ‘Stock Market Volatility: Roots and Results’, *Vikalpa*, 20(1), 1995, 37-48.
31. Schwert, G. W., ‘Stock Market Volatility’, *Financial Analyst Journal*, 46, 1990, 23-34.
32. Shenbagaraman, P., ‘Do Futures and Options Trading Increase Stock Market Volatility’?, Paper published as part of the NSE Research Initiative available at www.nseindia.com, 2003.
33. Tripathy, T. &Gil-Alana, L. A. , Review of Development Finance, 5(2), 2015, 91-97.
34. Wu, G., ‘The Determinants of Asymmetric Volatility’, *The Review of Financial Studies*, 14(3), 2001, 837-859.

35. Zakoian, J. M., ‘Threshold Heteroskedastic Models’, *Journal of Economic Dynamics*, 18(5), 1994, 931-955.
36. Zuliu, H.,”Stock Market Volatility and Corporate Investment”, IMF Working Paper, XIX, 1995, 1-26.

About Our Authors

Bedanta Bora is presently engaged as Head-Management Studies at Sikkim Manipal University, India. Graduated in Commerce from Gauhati University, India, he received his MBA degree from Tezpur Central University, India. He was awarded Ph.D by Gauhati University in 2010. Dr. Bora possesses 20 years of professional exposure. He has to his credit around 65^{+} research papers (select publications in Scopus) with participation in 16 professional workshops and 33 academic conferences held across the world. As far as global exposure is concerned, Dr. Bora has been abroad quite a few times in order to join and host International Conferences as a contributor, committee member, technical chair, invited speaker and delivered few key note address as well. He claimed some Best Paper Awards too.

Anindita Adhikary is currently a Professor in Management, Sikkim Manipal University, India**.** A commerce graduate from Gauhati University, India, she happens to be an MBA from Tezpur Central University, India and was awarded Doctorate by Gauhati University in 2009. Dr. Adhikary has 20 years of professional experience in academics and corporate sector. She has 60^{+} research publications (select papers in Scopus) to her credit and has been abroad a number of times in order to have an enriched exposure at international level. Dr. Adhikary had participated in 20 professional workshops and delivered talks as Guest Speaker at different Orientation Programmes initiated through National Productivity Council, MSME, Govt. of India and Department of Commerce. Govt. of Sikkim. Her domain of interest includes Finance and International Trade.