Print ISSN: 2288-4637 / Online ISSN 2288-4645
doi:10.13106/jafeb.2021.vol8.no4.0857

A Study on Unfolding Asymmetric Volatility: A Case Study of National Stock Exchange in India

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Received: December 20, 2020 Revised: March 07, 2021 Accepted: March 15, 2021

Abstract

The study aims to find the asymmetric effect in National Stock Exchange in which the Nifty50 is considered as proxy for NSE. A return can be stated as the change in value of a security over a certain time period. Volatility is the rate of change in security value. It is an arithmetical assessment of the dispersion of yields of security prices. Stock prices are extremely unpredictable and make the investment in equities risky. Predicting volatility and modeling are the most profuse areas to explore. The current study describes the association between two variables, namely, stock yields and volatility in equity market in India. The volatility is measured by employing asymmetric GARCH technique, i.e., the EGARCH (1,1) tool, which was used in building the study. The closing prices of Nifty on day-to-day basis were used for analysis from the period 2011 to 2020 with 2,478 observations in the study. The model arrests the lopsided volatility during the mentioned period. The outcome of asymmetric GARCH model revealed the subsistence of leverage effect in the index and confirms the impact of conditional variance as well. Furthermore, the EGARCH technique was evidenced to be apt in seizure of unsymmetrical volatility.

Keywords: Volatility, Asymmetric Effect, Conditional Variance, Nifty Index, India

JEL Classification Codes: C22, G10, G17

1. Introduction

Modeling and predicting volatility have become important topics for research and have gained prominence among academicians and researchers. This is due to the fact that instability is considered as a vital concept for pecuniary applications, like hedging, portfolio optimization, and pricing of assets. Volatility denotes the amount of risk about the variations in a security's price. A larger volatility means value can possibly fluctuate drastically whereas a lesser variability means a security value does not deviate considerably, but change happens over a period of time. Volatility in spot market is generally more visible in a falling market than in surging markets. Uptrend in the market tends to be gradual and downtrends have a tendency to be abrupt and sharper. Percentage change in price generally is higher in downward trend than in upward trend. A distinct characteristic of the volatility is that it is not directly noticeable, so analysts are particularly keen to find a detailed estimate of asymmetric volatility.

As soon as fluctuations in stock prices reach peaks, the repercussion can be catastrophic. Firstly, if such volatility exists, organizations may not be in a position to utilize the existing capital efficiently as large part of the cash-equivalents have to be maintained to restore confidence among lenders and regulators. Secondly, such type of volatility intensifies market-risk and necessitates market participants to maintain enough liquidity, thus bringing down the liquidity in the market completely. Finally, huge fluctuations dampen investors' confidence from carrying securities, thus guiding to demand for additional risk, which influences further volatility.

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Empirically, concomitant returns and conditional volatility are contrary, that is, positive earnings are normally accompanied with downward revisions of conditional volatility and vice versa. The pragmatic phenomena are stated as conditional variance in the literature. During stock market crashes existence of conditional variance is ostensible, when a huge decline in security price is related to a substantial surge in market variability (Wu, 2001; Christie, 1982). It reflects the relationship between variability and share price is the leverage effect.

The samples of time-series data are found to be dependent on their own historical values, based on past information and revealed in consistent variance. It was observed that volatility in market transforms along time and displays clustering of volatility. Subsequently, numerous tools were developed exclusively suitable to evaluate scedastic function, among them renowned and often used technique is the ARCH models. The key purpose of developing these models was to predict future volatility, which would accommodate more efficient portfolio allocation, to mitigate risk (Engle, 1982). ARCH is a tool employed to investigate volatility in time series. The GARCH technique recommended by Bollerslev (1986) is useful for assessing stochastic volatility. Nevertheless, GARCH cannot explain leverage effect, however it justifies for volatility clustering and leptokurtosis, which is inevitable to develop extended GARCH tools.

Abundant research has been carried out in developed countries to study the relationship between volatility and stock price, but minimal attention has been paid in emerging countries like India. It is now notable that equities in emerging markets have diverse features than that of equities from advanced markets.

The purpose of the paper was to examine the changing facets of volatility in equity earnings in National Stock Exchange (NSE) during the study period 2011 to 2020. Many structural changes and reforms were taken place in the country during the period, such as demonetization of currency, goods and services tax, slowdown in the economy and disastrous Covid-19, which are likely to effect unpredictability in returns. The markets in the country witnessed record highs by end of 2020, an empirical study at this juncture is appropriate and useful.

2. Literature Review

Jorge (2004) modeled the fluctuations in PSI-20 for the daily and weekly returns using ARCH family models and observed noteworthy lopsided surprises to variability in the returns and not witnessed on weekly yields. Bekaert and Wu (2000) show that volatility at firm level was improved by strong asymmetries in scedastic function but not witnessed at market level. Balaban's (2005) study put forward that when compared to GJR GARCH, EGARCH was a better model in envisaging forex rate volatility. Hansen and Lunde (2006) observed that APARCH technique provides superior forecasts to that of parsimonious GARCH models.

Karmakar (2007) observed that volatility rises high during market fall and study also witnessed returns are not considerably correlated to risk. Alberg et al. (2008) suggests exponential GARCH is highly effective in predicting TASE Indices. Jayasuriya et al. (2009) investigated conditional variance for three sub-periods on several developing and advanced markets. Majority of the markets divulges high degree of asymmetric volatility.

Srinivasan and Ibrahim (2010) tried to predict the fluctuations in Sensex yields of equity market in India. In spite of incidence of leverage effect, symmetric models executed well in estimating conditional variance rather than the asymmetric class of models, which was exhibited from the study.

Chiang and Huang (2011) study observed that GARCH model fits better in bull markets while nonlinear GARCH model is appropriate in bearish markets. Malik (2011) shows that, by accounting structural breaks in the model, variability can be minimized by good surprises and also volatility persistence. Baur (2012) demonstrated that positive surprises cause more volatility than negative shocks.

Kristoufek et al. (2014) studied the effect of leverage on energy futures and observed that yield and variability have opposite relationship on all the contracts considered, except for natural gas. Lama et al. (2015) study evidenced that EGARCH tool outpaced in predicting the global cotton prices because of the ability in annexing unsymmetrical variability. Uyaebo et al. (2015) revealed that volatility in Nigerian and Kenya stock earnings react to market shocks compared to rest of the countries. The results point to a lack of leverage effect in both countries, but it present in rest of the nations in the study.

Prateek and Vipul (2015) observed that linear GARCH model performed better compared to non-linear GARCH tools. Ndwiga and Muriu (2016) study observed volatility surprises on the returns are temporary in the equity markets and have not witnessed any noteworthy leverage effect. Bradley and Malik (2017) found the good and bad shocks have considerable effect on fluctuations in returns if breakups in the structure are described in the linear GARCH class model. Jeffery et al. (2017) found that extended GARCH models are better fit for estimating the volatility in crypto currencies. Harpestad et al. (2019) confirmed the equity markets around the world revealed contingent variance. Katsiampa (2019) found similarities in crypto currency markets. In addition, the study also proved that Ether can be worthwhile risk management tool in the case of Bitcoin. Two crypto currencies unsymmetrical variance and correlation are reactive to major shocks.

Herbert et al. (2019) show the leverage effect was witnessed in Nigerian stock market. Raja Babu et al. (2020)

concluded that negative surprises cause superior volatility to that of positive surprises in banking index. Samineni et al. (2020) observed the existence of conditional variance in Nifty Bank Index. Thanatawee and Yordying (2020) revealed there exists inverse relationship between foreign affiliates and equity price fluctuations. Napon and Asama (2020) found negative surprises have more effect on volatility in both stock markets.

3. Research Methodology

3.1. Source of Data

The current study was purely confined to secondary source of information, which was gathered from official website of National Stock Exchange. Nifty50 index was proxy to the NSE. The closing values of Nifty50 were collected during the period from January 1, 2011, to December 31, 2020, was used for analysis.

3.2. Statistical Tools

Volatility has been measured on returns (R_t) and daily returns on index were computed prior to diagnostic check. The Nifty return series was computed as a natural logarithm of 1st difference of closing values, which is as follows:

$$r_t = \log \frac{P_t}{P_{t-1}} \quad (1)$$

Wherein R_t is the natural log of Nifty return at period t, P_t is value at period t, and P_{t-1} is the price at period $t-1$.

3.3. Unit Root Test

The unit root for the time series data have been checked for Nifty index using ADF test statistic. Test for heteroscedasticity, need to be applied in the residuals before moving to further analysis. Lagrange Multiplier (LM) test is used to test heteroscedasticity in the residuals on Nifty returns.

3.4. Volatility Measurement Technique

For modeling asymmetric effect exponential GARCH (1, 1) was used.

3.5. Exponential GARCH Model

The asymmetric effect can be substantiated and the tool permits to capture the asymmetries in the Indian equity market (Nelson, 1991) and henceforth the resulting formula:

$$\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{\pi}{2}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (2)$$

The left side is the logarithm of conditional volatility. The constant is nothing but asymmetric term. If $P = 0$, represents symmetric. If it is considerable and negative, which specifies existence of the leverage effect.

4. Results

To convert the series into stationary, first differencing tool was used on the closing values of Nifty, which is a proxy for Indian market. Figure 1 illustrates clustering of volatility of Nifty50 during ten years period. It is surmised that large variations in variance of returns for prolonged period of time and small changes in log prices for over extended time period, which infers the volatility is clustering, but variance may vary with time.

Descriptive statistics of the study are summarized in Table 1. Mean of the Nifty returns is positive, signifying that the price increased during the period. Sign of negative skewness, specify that there is possibility of earnings greater than mean. Kurtosis greater than three, sign of leptokurtic nature and furthermore Jarque-Bera statistics was 292.8, which is statistically significant and henceforth residuals are normal in the distribution.

Table 2 depicts Augmented Dickey Fuller test that is applied to find unit root in the data. ADF statistic value is below 5% level, which reveals that data considered for the period is stationary. Hence, the outcome confirms the stationarity in the series. The Lagrange Multiplier test is used to identify heteroscedasticity in the residuals. Test results from Table 3 are highly noteworthy. As the p-value is lower than 5%, alternative hypothesis is accepted, which signifies existence of arch effect in the residuals and henceforth the outcome documents the assessment of non-linear GARCH model. Therefore, the EGARCH model is applied for modeling the volatility of return in the index.

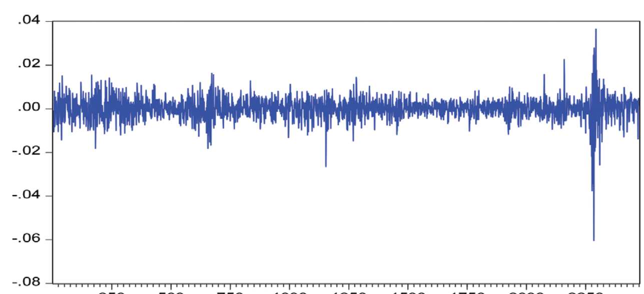
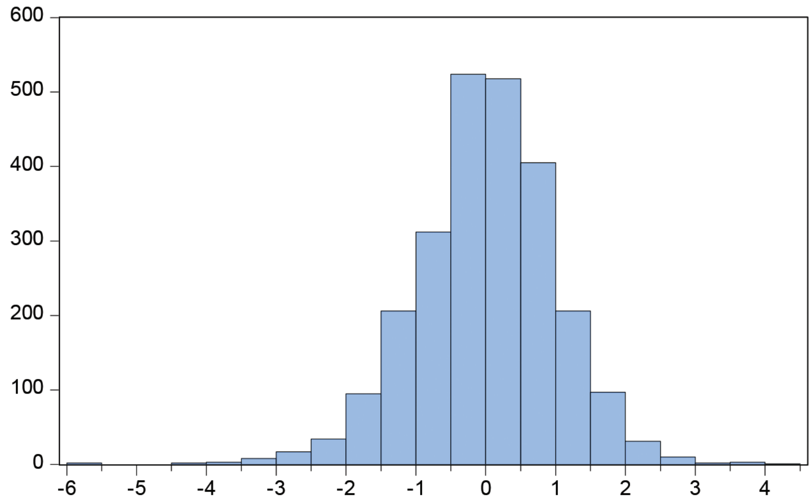


Figure 1: Line Diagram of Nifty Returns

Table1: Histogram of Nifty Return Series



Series: Standardized Residuals
Sample 2 2477
Observations 2476

Mean	0.004966
Median	0.028153
Maximum	4.304864
Minimum	-5.750704
Std. Dev.	1.000081
Skewness	-0.331541
Kurtosis	4.548918
Jarque-Bera	292.8719
Probability	0.000000

Table 2: Results of Stationarity Test in Residuals

		***t*-Statistic**	**Prob.***
Augmented Dickey-Fuller test statistic		–49.36509	0.0001
Test critical values:	1% level	–3.432798	
	5% level	–2.862507	
	10% level	–2.567330	

Table 3: ARCH-LM Test for Residuals

F-statistic	76.84644	Prob. *F*(1,2473)	0.0000
Obs**R*-squared	74.59074	Prob. Chi-Square (1)	0.0000

Table 4: Heteroskedasticity Test: ARCH

F-statistic	1.562859	Prob. *F* (1,2473)	0.2114
Obs* *R*-squared	1.563135	Prob. Chi-Square (1)	0.2112

Table 5: Outcome of EGARCH (1,1) Model

Variable	**Coefficient**	**St. Error**	***z*-Statistic**	**Prob.**
C	0.000120	7.21E-05	1.664658	0.0960
Variance Equation				
C(2)	–0.330258	0.039608	–8.338093	0.0000
C(3)	0.112840	0.014248	7.919634	0.0000
C(4)	–0.098608	0.006545	–15.06688	0.0000
C(5)	0.977823	0.003155	309.9087	0.0000

However, the ARCH-LM test is used on residuals and results exhibited in Table 4 that there is absence of arch effect during the study period.

The Exponential GARCH class technique is employed to calculate the Nifty returns and the outcome is exhibited in Table 5. The results disclose the sum of α and β coefficients are more than one, stating that scedastic function is volatile. The leverage constant (γ), is negative and noteworthy, unveiling unsymmetrical effect on return in the study. The empirical study divulges that the relationship amid past and future returns is negative.

5. Conclusion

In the current research, by using asymmetric GARCH model, volatility in NSE index returns was checked. The time-series data used for the study was made stationary using first differencing technique. ARCH effect is present in the data set. Performance of market and volatility have a sturdy relationship. Fluctuations tend downward when the stock market surges and intensify when market falls. In Exponential GARCH tool, the sum of constants ($\alpha + \beta$) is greater than one meaning that the market is highly volatile. The asymmetric parameter (γ) is considerably negative, which suggests the survival of leverage effect, i.e., positive information has less impact on scedastic function than negative surprises.

References

Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics, 18*(15), 1201–1208. https://doi.org/10.1080/09603100701604225

Balaban, E., & Bayar, A. (2005). Stock returns and volatility: empirical evidence from fourteen countries. *Applied Economics Letters, 12*(10), 603–611. https://doi.org/10.1080/13504850500120607

Baur, D. G. (2012). Asymmetric volatility in the gold market. *The Journal of Alternative Investments, 14*(4), 26–38. https://doi.org/10.3905/jai.2012.14.4.026

Bekaert, G., & Wu, G. (2000). Asymmetric volatility and risk in equity markets. *The Review of Financial Studies, 13*(1), 1–42. https://doi.org/10.1093/rfs/13.1.1

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics, 31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Caiado, J. (2004). Modelling and forecasting the volatility of the Portuguese stock index PSI-20. *Estudos de Gestão, 9*(1), 3–22. http://hdl.handle.net/10400.5/9973

Chiang, M. H., & Huang, H. Y. (2011). Stock market momentum, business conditions, and GARCH option pricing models. *Journal of Empirical Finance, 18*(3), 488–505. https://doi.org/10.1016/j.jempfin.2011.01.004

Christie, A. A. (1982). The stochastic behaviour of common stock variances: Value, leverage and interest rate effects. *Journal of Financial Economics, 10*(4), 407–432. https://doi.org/10.1016/0304-405X(82)90018-6

Chu, J., Chan, S., Nadarajah, S., & Osterrieder, J. (2017). GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management, 10*(4), 17. https://doi.org/10.3390/jrfm10040017

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987–1007. https://doi.org/10.2307/1912773

Ewing, B. T., & Malik, F. (2017). Modelling asymmetric volatility in oil prices under structural breaks. *Energy Economics, 63*, 227–233. https://doi.org/10.1016/j.eneco.2017.03.001

Hansen, P. R., & Lunde, A. (2006). Consistent ranking of volatility models. *Journal of Econometrics, 131*(1-2), 97–121. https://doi.org/10.1016/j.jeconom.2005.01.005

Herbert, W. E., Ugwuanyi, G. O., & Nwaocha, E. I. (2019). Volatility clustering, leverage effects and risk-return trade-off in the Nigerian stock market. *Journal of Finance and Economics, 7*(1), 1–13. https://doi.org/10.12691/jfe-7-1-1

Hongsakulvasu, N., & Liammukda, A. (2020). Asian Stock Markets Analysis: The New Evidence from Time-Varying Coefficient Autoregressive Model. *Journal of Asian Finance, Economics and Business, 7*(9), 95–104. https://doi.org/10.13106/jafeb.2020.vol7.no9.095

Horpestad, J. B., Lyócsa, Š., Molnár, P., & Olsen, T. B. (2019). Asymmetric volatility in equity markets around the world. *The North American Journal of Economics and Finance, 48*, 540–554. https://doi.org/10.1016/j.najef.2018.07.011

Jayasuriya, S., Shambora, W., & Rossiter, R. (2009). Asymmetric volatility in emerging and mature markets. *Journal of Emerging Market Finance, 8*(1), 25–43. https://doi.org/10.1177/097265270900800102

Karmakar, M. (2007). Asymmetric volatility and risk-return relationship in the Indian stock market. *South Asia Economic Journal, 8*(1), 99–116. https://doi.org/10.1177/139156140600800106

Kristoufek, L. (2014). Leverage effect in energy futures. *Energy Economics, 45*, 1–9. http://dx.doi.org/10.1016/j.eneco.2014.06.009

Lama, A., Jha, G. K., Paul, R. K., & Gurung, B. (2015). Modelling and forecasting of price volatility: An application of GARCH and EGARCH models. *Agricultural Economics Research Review, 28*(347-2016-17165), 73–82. https://doi.org/10.5958/0974-0279.2015.00005.1

Malik, F. (2011). Estimating the impact of good news on stock market volatility. *Applied Financial Economics, 21*(8), 545–554. https://doi.org/10.1080/09603107.2010.534063

Ndwiga, D., & Muriu, P. W. (2016). Stock Returns and Volatility İn An Emerging Equity Market. Evidence from Kenya. *European Scientific Journal, 12*(4), 79. https://doi.org/10.19044/esj.2016.v12n4p79

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica: *Journal of the Econometric Society,* 347–370. https://doi.org/10.2307/2938260

Raja Babu, P., Kumar, S. R., & Naganjaneyulu, A. V. (2020). Modeling Asymmetric Volatility: Evidence from India. *Journal of Critical Reviews, 7*(9), 845–850. https://doi.org/10.31838/jcr.07.09.158

Samineni, R. K., Puppala, R. B., Muthangi, R., & Kulapathi, S. (2020). Expiration-Day Effects on Index Futures: Evidence from Indian Market. *Journal of Asian Finance, Economics and Business, 7*(11), 95–100. https://doi:10.13106/jafeb.2020.vol7.no11.095

Sharma, P. (2015). Forecasting stock index volatility with GARCH models: international evidence. *Studies in Economics and Finance*. https://doi.org/10.1108/SEF-11-2014-0212

Srinivasan, P., & Ibrahim, P. (2010). Forecasting stock market volatility of BSE-30 index using GARCH models. *Asia Pacific Business Review, 6*(3), 47–60. https://doi.org/10.1177/097324701000600304

Thanatawee, Y. (2021). The Impact of Foreign Ownership on Stock Price Volatility: Evidence from Thailand. *Journal of Asian Finance, Economics and Business, 8*(1), 7–14. https://doi.org/10.13106/jafeb.2021.vol8.no1.007

Tripathy, N., Rao, S. R., & Kanagaraj, A. (2009). Impact of derivatives trading on spot market volatility: an empirical study. *International Journal of Applied Decision Sciences, 2*(2), 209–232. https://doi.org/10.1504/IJADS.2009.026553

Wu, G. (2001). The determinants of asymmetric volatility. *The Review of Financial Studies, 14*(3), 837–859. https://doi.org/10.1093/rfs/14.3.837

Katsiampa, P. (2019). Volatility co-movement between Bitcoin and Ether. *Finance Research Letters, 30*, 221–227. https://doi.org/10.1016/j.frl.2018.10.005

Uyaebo, S. O., Atoi, V. N., & Usman, F. (2015). Nigeria stock market volatility in comparison with some countries: Application of asymmetric GARCH models. *CBN Journal of A*pplied Statistics, 6(2), 133–160. http://hdl.handle.net/10419/142109