Innovations

Asymmetric Volatility Structure: A Study on Indian Stock Exchange

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***Abstract**: The goal of this study is to investigate the persistence and asymmetric volatility structure of the Indian stock market based on the collected data from January 2002 to March 2022. The purpose of this strategychooses daily, weekly, and monthly return prices of Nifty 50 as the benchmark of the Indian equity market. Severalsymmetric and asymmetric variations of the GARCH family model were usedto evaluate thevolatility dynamics. We showed Engle and Ng Joint test "results, that serve as good justification for estimating GARCH model which allows for Asymmetric volatility. Our results demonstrate thatNifty 50 daily and weekly price series are found to respond to good and bad news asymmetrically, but not likely in monthly returns. Similarly, we observed that volatility is highly persistent in daily and weekly returns, and the effect of shocks disappearsover the period when the data set is extended. However, this stylistic fact indicates that past volatility is having a significant impact on future volatility and the emergence of unfavourable news in the market constantly impacts investors' emotions and behaviour patterns.These results are important for policymakers, fund managers, and investors for hedging and diversifying their portfolios to understand the sentiment of the market.*

***Keywords:** Asymmetric, Volatility, Garch model, stock market, shocks*

1. Introduction

The Indian economy is one of the most rapidly changing economies in the world. This has become possible because of global trade,and the increasingly global integration of equity markets due to technical developments and the withdrawal of financial regulations.In addition to this, national stock markets are booming consolidated due to the increasing presence of international investors. Strong links between the domestic and global financial markets and related fast-paced developments continue to generate interest among researchers, academicians, and regulators on how to evaluate financial risk models. The integrated stock market provides opportunities for investors to invest in domestic market to diversify their risk andget benefits such as an increase in investment and a decrease in transaction cost,helpful in the growthof the economy ((Bae & Zhang, 2015; Vo & Ellis, 2018).The Country's booming economy is likely to experience more ups and downs, including movement in the equity market. Movement in the equity market denotes volatility and volatility is associated with risk.

Several studies have been conductedto establish the association between the stock market performance and volatility and some of them found that high volatility is associated with higher opportunities in a declining market, while low volatility is associated with higher opportunities in a growing market. Volatility to stock prices response to new information quickly. Black (1976), Christie (1982), Hentschel (1992), Sentena (1992),Campbell and, Nelson (1991), Engle and Ng (1993) and Pagan and Schwert (1990) haveconfirmed that shocks impact volatility of return.

These factors make it critical to comprehend the volatility of the Indian stock market because we cannot generalize the one volatility return across the other markets. Indian equity market isone of the fastest engines for future growth. Stock market share to GDP (%) in India was reported at 98.95% in 2020, according to the World Bank's development index, compiled from officially recognized sources. Despite the relevance of emerging markets, there is very little amount of study conducted in this area. Most of the studies focused on the Asian stock market and other developed market with different modeling structure.

In this study there is an attempt to test the influence of news on stock volatility in the Nifty 50 index. The main interest is to evaluate whether the volatilityin stocks can be because of shocks (good or bad news). To do this, we estimated the variant of GARCH family model with different time frequencies (daily, weekly, and monthly) to ascertain the dynamics of volatility. We also employed joint sign and size bias test for the best justification of the asymmetric volatility. The results indicated that asymmetric coefficient of variance is statistically significant in daily and weekly price series. No such evidence was found in case of the monthly price return. This shows that the advent of news in the market continuously impacts investors' sentiment and behaviour patterns in short time frame. The rest of the paper is arranged as follows. The second Section reviews both theoretical and empirical literature. The methodology, and the description of the data isstated in Section 3. Section 4 discuss the empirical result and analysis followed by Section 5, which finishes the study.

2. Literature Review

The property of asymmetric volatility was first recognized by the Black (1976) which suggested that negative news has a great impact on the volatility of return as compared to the positive news which shows that the bigger the magnitude of the shock to the variance the higher the volatility. Plenty of studies have been conducted across the globe using the variant of the GARCH family modelto overlookthe asymmetric volatility structure of financial time series (Bekaert & Wu, 2000; Shambora, & Rossiter, 2009; Talpsepp& Rieger, 2010; Horpestad et.al., Molnár, & Olsen, 2019; Iqbal, Manzoor, & Bhatti, 2021).

Most of the researchers discovered that asymmetric variants of GARCH models such as EGARCH, GJR-GARCH, APARCH, etc. havehigher predictability than simple OLS and symmetric GARCHmodels ((Pagan &Sossounov, 2003), (Awartani & Corradi, 2005), (Balaban & Bayar, 2005), (Hansen & Lunde, 2006) (Karmakar (2007)). Erdogdu examines the volatileeffect in the Europe index using electronic market high-frequency spot price data. The Result employ the T-GARCH and EGARCH modelsto check the magnitude effectandconfirm that the persistence exists in seasonal return. Pece and Petra (2015) usedthe data of Romania stock exchange from the period 2004 to 2012 to determine the volatility persistence and asymmetric. Moghadam (2010) examined the multivariate GARCH model to check the relationship between NASDAQ, S&P 500, and WTI daily oil price. The Result confirms the response of the shock persistence of the stock market to oil price return.

Jorge (2004) analyzed the ARCH models to calculate daily and weekly returns and found volatility structure in daily pricesbut not on weekly data. Balabans (2005) extended the study by using GJR GARCH,and E Garch model to check the foreign exchange market volatilityand found a positive response. Dennis et al. (2006) and Hansen et al. (2006) compare the APARCH and GARCH model and result confirm that forecasting volatility with APARCH provides better results to GARCH model. Bose (2007) analysed the NSE Nifty and future prices to predict the impact of volatility and the result conclude the dominance of future market. A Number of studies Alberg (2008) Jayasuriya et al.(2009), Olove (2009) Srinivasan and Ibrahim (2010), Talpsepp and Rieger(2010) examine the volatility characteristics of the equity market using the E-GARCH model. The Result confirms that the impact of negative asymmetric volatility is present, and persistence is high which shows there is a positive relation between the past variance and current variance. Fleming et al., (1995), low, C. (2004), Bollerslev (2006), Dennis et al., (2006), fernandas et al., (2014), and Smales (2016) worked on the relationship between volatility index and stock market return on US data exchange. Dennis et al., (2006) identified the primary cause of asymmetric volatility in the return.Karmakar (2007) observed the existence of volatility and revealed that there is an inverse relationship between the market mood and the stock return. when market mood is off the volatility in the return expected high.Mohanty (2009) Bordoloi and Shankar (2008) explored volatility of four Indian stock market indices using TGARCH and EGARCH models.

Yaya and Alana, (2014) examined the impact of asymmetric behaviour in the Nigerian market during both the bullish and the bearish periods. Can and Wang (2019) reported the existence of asymmetric volatility persistence and their results confirmed that the coefficient of negative shocks ishaving more impact than the positive ones. It is interesting to notethis theoretical evidenceand raise the scope of the asymmetric volatility persistence and volatility feedback effect in the Indian stock market.

3. Research methodology

Thisresearch is intended to examine the volatility structure of the Indian stock market. We choose the nifty 50 as the benchmark of the Indian stock market because approximately 65% of the floated-adjusted market capitalization of NSE is captured by the nifty 50, therefore the index itself represents the true reflection of the stock market. The closing price (daily, weekly, and monthly) of Nifty 50 is taken from the official site of NSE covering the 20 years of data collection from January 1, 2002, to March 31, 2022.

Once we capture all the required data thenit is necessary to compute continuously compounded daily, weekly, and monthly price returnsas a natural logarithm of 1st differencing of closing value. Log transforming of data is helpful in stabilize the variancewhich is as follows:

$$R = \log P_t - \log P_{t-x} \qquad \text{..... (1)}$$

Where,the Natural log of Nifty return is represented by R and period t, x is the 1,5 and 10 which is the observation ofdaily,weekly, and monthly return, andP_t is the value at period t.

Before estimating the GARCH models of the financial data we need to check the stationarity of the price of the data. The stationarity of the data diagnosed by the ADF test because data must satisfy the pre-condition to apply the GARCH model.

3.1 GARCH and Extension of GARCH Modelling

We continued with GARCHmodeling for analyzing the three frequencies (daily, weekly, and monthly).The GARCH (generalized autoregressive conditional heteroskedasticity) model is an approach to capture the volatility structure in data (Salisa and Gupta,2021) developed in 1982 by Robert F. Engle.

$$ht = \alpha o + \sum_{i-1}^{q} \alpha_i \, \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \, h_{t-j} \qquad \text{.....(2)}$$

In this equation, where $\alpha 0 > \alpha 1 \geq 0$ and I = 1,2, q, and β j ≥ 0, and j = 1,2, p. Hence, the GARCH model proves to be more effective than the ARCH model because it accounts for the impact of past errors. This formulation better captures volatility clustering in financial asset return data, as heightened volatility in previous periods leads to forecasts predicting increased volatility in subsequent periods.

3.1.1. **GJR-GARCH**

The GJR model, introduced by Glosten, Jagannathan, and Runkle (1993), is an asymmetric variant of the GARCH model. Unlike traditional GARCH models, the GJR model permits the variance to respond disparately based on the direction and magnitude of the received shock. While the conditional mean equation remains consistent with prior ARCH-GARCH models, the formulation for the conditional variance is modified to accommodate asymmetric volatility. The generalized specification for the conditional variance is as follows:

$$\sigma_t^2=\omega+\alpha\varepsilon_{t-1}^2+\gamma\varepsilon_{t-1}^2 I_{t-1}+\beta_1\sigma_{t-1}^2 \qquad \text{...... (3)}$$

where $I_{t-1}= 1$ if $\varepsilon_{t-1}< 0$ and otherwise 0. If γ is positive and statistically significant, this is the evidence of the leverage effect. Also, don't forget non-negativity restraint: ω, a_1, and β must be positive. However, γ can be negative if $(\alpha + \gamma)> 0$.

3.1.2. E-GARCH

Nelson (1991) proposed the Exponential GARCH model. This model removes the non-negativity constraint and captures the influence of both positive and negative shocks. This conditional variance equation appearsmuch more complicated than the previous model. The key coefficient to look at is + γ.

$$log h_t=\omega + \beta log h_{t-1} + \gamma \frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}+\alpha_i \left\{\left|\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}}\right|-\sqrt{2}/\pi\right\} \qquad \text{....(4)}$$

Here, ω is a constant, εt is the innovation or the shock process, ht is the conditional standard deviation. $\alpha\&\beta$ respectively are the ARCH and GARCH parameters. γ is the leverage parameter. If γ is statistically significant and has a negative sign, this implies that a fall in return result is greater volatility than the increase in returns of the same magnitude (leverage effect).

After estimating the GARCH (1,1) model, we analysed the following step to determine theJointsign and size bias test. Sign Bias tests would help us to verifywhether the good news and bad news have differently impact on the future volatility. The size bias variance would investigate whether the magnitude of the shock also affects the future volatility. The final equation for the estimation would be as follows.

$$\varepsilon_t^2 = \emptyset_0+\emptyset_1 s_{t-1}^-+\emptyset_2 s_{t-1}^-\epsilon_{t-1}+\emptyset_3 s_{t-1}^+\epsilon_{t-1}+\gamma_t \qquad \text{.... (5)}$$

whereε_t^2 is the squared residual of a GARCH model fitted to the return, $\gamma_t$is an error term,

$\emptyset_0$is a constant, ands_{t-1}^- is a dummy variable that takes value 1.

4. Findings and Discussion

4.1 Unit Root Test

Before estimating the parameters of the volatility model, we applied the ADF test to check the stationarity of the price data. The results are reported in Table 1. which shows that the critical value of the return data is statistically significant at 1 %. Hence, we don't findany problems of a unit root in our data.

Table 1. Test for Stationarity

	T-Statistics	Probability*
Augmented Dickey-fuller test (ADF)	-67.75609	0.0001

4.2. Volatility Measurement Technique

We analyse the symmetric variant of the GARCH family model. In Table 2. columns 1, 2, and 3 represent the result of Daily GARCH, GJR GARCH and E-GARCH model. The parameters of variance equations of GARCH (11) model show that the coefficient of daily return is statistically significant implying that the new information coming into the market has a significant impact on predicting the intraday spill over. Because due to some constraints in model, we do not confirm any asymmetric volatility effect by this process. Therefore, we also assess the GJR-GARCH and E-GARCH equations. The result reveals that the coefficient of the βeta is positive and statistically significant at 1% which implies that the impact of negative shock has significantly higher impact than the impact of positive shock on return volatility. Similarly, we have evidence that all the parameters of the E-GARCH regression are significant, confirming that persistence and asymmetrically volatility are present in the following period.

Table 2. GARCH, GJR-GARCH and EGARCH (Daily)

	GARCH	**T-GARCH**	**E-GARCH**
	Mean Equation		
C	0.000865***	0.00055***	0.000511***
AR(1)	-0.161228***	-0.110283***	0.029628***
MA(1)	0.232126***	0.193096***	0.057945***
	Variance Equation		
α_0	2.40E-06***	2.96E-06***	-0.357728***
α_1	0.104728***	0.040685***	0.200186***
γ		0.11942***	-0.090248***
β1	0.885311***	0.883764***	0.977099***

Note: Symbols ***, **, and * signify rejection of the null hypothesis at significant levels of 1%, 5%, and 10%, respectively

Table 3.Sign and size Bias joint test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.88E-05	1.96E-05	1.974793	0.0483
DUMMY1	-9.91E-06	2.74E-05	0.361457	0.7178
DUMMY1*GARCH11RES(-1)	-0.019243	0.001298	14.82276	0***
DUMMY2*GARCH11RES(-1)	0.014823	0.001489	9.953113	0***

Note: Symbols ***, **, and * signify rejection of the null hypothesis at significant levels of 1%, 5%, and 10%, respectively.

The results in Table 3 represents the asymmetric joint sign and size bias test.The estimatedcoefficient for s_{t-1}^{-}, $\emptyset_0$has a p-value of 0.7178 which is more than critical value demonstrates that it is insignificant. It does not indicate the strong sign bias. The estimated coefficient for $s_{t-1}^{-}\epsilon_{t-1}$ and $s_{t-1}^{+}\epsilon_{t-1}$are both significant with p-values of 0.000 and 0.0000 respectively. This is a strong indicator of size bias.Thus, we deduce that the future volatility is not affected differentially by positive and negative shocks. However, the notable finding regarding size bias demonstrates the existence of shock magnitude in volatility.

Table 4. GARCH, GJR-GARCH and EGARCH (weekly)

	GARCH	**T-GARCH**	**E-GARCH**
	Mean Equation		
C	0.003255***	0.002291***	0.002105***
AR(1)	0.341635***	0.521169***	0.518772
MA(1)	-0.282605***	-0.440956***	-0.443486***
	Variance Equation		
α_0	4.51E-05***	4.62E-05***	-0.744652***
α_1	0.168798***	0.078205***	0.297394***
γ		0.174623***	-0.111656***
$\beta 1$	0.780392***	0.781120***	0.929680***

***, ** and * respectively indicates rejection of null hypothesis at 1%, 5%, and 10% significant level.

In further analysis, we repeated all these steps in case of weekly and monthly returns. The stationarity of these two frequencies was established by the unit root test. The results of GARCH estimates in case of weekly data aredisplayed in Table 4 displays statistically significant coefficients for all parameters at a certain p-value threshold. Moreover, it highlights that the volatility of the current week has a notable impact on the volatility of the subsequent week. Additionally, both the TGARCH and EGARCH models exhibit significant coefficients across all variables, implying the presence of asymmetries in weekly volatility data.Based on the results, it is concluded that in comparison to good news, the magnitude of the negative news has more impact on returns'and affects the volatility over a week. The significant coefficients of the Joint size and sign bias test were also helpful in reconfirming the results of the study.But in monthly data, all estimates were found insignificantas there was no ARCH effect which further nullified the application of GARCH model.The conclusion drawn suggests that in the context of monthly returns, volatility doesn't persist over time but rather diminishes. This observation aligns with the efficient market hypothesis, which posits that asset prices reflect all available information and adjust rapidly to new information. In this scenario, the efficient market theory suggests that any news or information impacting the market is quickly absorbed and reflected in prices, leaving little room for persistent volatility in monthly returns. This supports the notion that markets efficiently incorporate news and information over relatively short periods of time.

5. Conclusion

In this study, by using the variant of GARCH family model, volatility structure of the Nifty 50 index of Indian stock market was checked. The joint sign and size bias was applied for examining the impact of shocks on volatility. Our findings primely help us in concluding the result that standard GARCH (11) model continued with ARCH effect of all the three frequencies (daily, weekly, and monthly) price data but the volatility of the stock return positively captured in only daily and weekly price data. We used GJR model to estimate the asymmetric (leverage effects) to know the identical impact of good news and bad news. However, the outcome indicated that the impact of negative news is completely reflected in the price of the daily and weekly data, demonstrating that the volatility of the present daily and weekly data does influence the volatility of the following day and the following week's return.We found that persistence level is also very evident in daily and weekly return by estimating EGARCH model. We could not validate any shocks effects and persistence in monthly price data because we believe by the passage of time sentiment of the investor toward the positive and negative shocks faded away. These finding support that investor can use this information on long term stock market volatility to align their portfolio with associated expected return.

JEL Classification Codes: C53,C32, G11, C58

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