European Economic Letters
ISSN 2323-5233
Vol 14, Issue 1s (2024)
http://eelet.org.uk

ANALYSING THE IMPACT OF VOLATILITY DECAY ON FORECASTED RETURNS USING ARMA, SYMMETRIC AND ASYMMETRIC GARCH AND TGARCH MODELS

Dr. Archana Agarwal*
Associate Professor, Department of Commerce,
Sri Aurobindo College (Evening),
University of Delhi

Nidhi Dhankhar
Research Scholar,
Institute of Business Management and Agripreneurship, Gurugram,
CCS HAU

ABSTRACT
In accordance with the general perception that the risk appetite of an investor determines his reward, the discussion neglects the important issue of the impact of volatility. An informed investor is able to take the right decisions and create a portfolio that maximizes returns. Academics, however, engage themselves to understand the volatility by employing empirical analysis and provide evidence-based results. The current research identifies sixteen sectoral indices of the National Stock Exchange of India (NSE). A combination of Autoregressive Moving Average (ARMA) and Generalized Autoregressive Conditional Heteroskedastic (GARCH) and T-GARCH (Threshold-GARCH) have been applied to the closing price of indices from Jan. 1, 2019 until January 31, 2024. The returns on each of these indices have been forecasted for the next three months ending on April 30, 2024. The outcome of the research shows that news and information have a direct bearing on the returns of the indices. Moreover, the negative shocks in the previous period have more volatility than the positive shock of the same magnitude illustrating an inverse relationship between volatility decay rate and future returns.

Keywords: Volatility, News Impact, Risk and Return, GARCH, Sectoral Indices

JEL Codes: C580, G11, G17

1. Introduction

Volatility, the variability in returns, holds significant importance in derivative pricing, risk management and the formulation of hedging strategies. Moreover, comprehending volatility is pivotal in constructing an optimal portfolio as it mirrors the consistent behavior of the stock market (Mukherjee & Goswami, 2017; Mittal & Goyal, 2012). Investors aim to mitigate risk and maximize returns, which can be achieved through studying market volatility (Tabassum, et al., 2023) and employing forecasting techniques (Idrees, et al., 2019).

Different techniques for forecasting variance in a stock market have been used by investors, researchers and institutions. The most commonly used are ARCH-GARCH Models (Autoregressive Conditional Heteroskedasticity-Generalized Autoregressive Conditional Heteroskedasticity). These models underscore the persistence of volatility shocks, emphasizing the importance of current information in predicting conditional variance across all time frames (Engle & Bollerslev, 1986). They have proven effective in forecasting volatility in time-series data characterized by implicit heteroskedasticity or time-varying variance. Specifically, the GARCH model (Bollerslev, 1986) adeptly captures the attributes of fat-tailed distribution by identifying volatility clusters, non-linear patterns and symmetric and asymmetric effect on high frequency financial series. Overtime, additional models for volatility modelling have been introduced which include the GARCH-in-Mean (GARCH-M) (Engle, et al., 1987), the Exponential-GARCH (EGARCH) (Nelson, 1991), and the Threshold-GARCH (TGARCH) (Zakoian, 1994; Wang, et al., 2022).

Several studies have investigated volatility modelling using both symmetric and asymmetric GARCH models (Onali, 2020; Awalludin, et al., 2018; Chang, et al., 2012; Alberg, et al., 2008). The scope of volatility modelling and forecasting is broad, extending to various domains including the analysis of volatility in exchange rates (Marreh, et al., 2014), in future and spot returns (Arora & Dang, 2019), returns on stock indices (Idrees, et al., 2019), stock returns (Sen, et al., 2021) and sectoral index returns (Khera, et al., 2022).
Malik and Hassan (2004) identified the effect of volatility shift (caused by political or economic events) on shock persistence by introducing endogenously determined break points or dummy variables in GARCH model and

* Corresponding Author

European Economic Letters
ISSN 2323-5233
Vol 13, Issue 3 (2023)
https://doi.org/10.52783/eel.v13i3.331
http://eelet.org.uk

concluded that volatility persistence is considerably reduced when these endogenously determined volatility shifts are used.

Karmakar (2005) applied the GARCH (1,1) model to BSE Sensex (Bombay Stock Exchange) data and concluded its suitability for the Indian stock market, while also highlighting the importance of utilizing asymmetric models to capture market volatility effects. Subsequently, Padhi (2006) and Karmakar (2007) further explored volatility characteristics in the Indian stock market using EGARCH and GJR-GARCH (Glosten-Jagannathan-Runkle GARCH also known as TGARCH) models, revealing evidence of time-varying volatility and asymmetric effects (Glosten, et. al., 1993). Efforts have also been made to model return volatility in other markets, such as the Nigerian stock exchange by Adesina (2013), confirming volatility persistence but not finding evidence of the leverage effect or risk-return trade-off.

Similarly, Mallikarjuna and Rao (2017), Bhatia and Gupta (2020), and Anoop, et al. (2018) have examined volatility in different market sectors and during specific events, showcasing the varied impacts and persistence of volatility.
More recent studies, such as those by Nikhil et al. (2023), Meher et al. (2021), Vasudevan and Vetrivel (2016) continue to explore volatility dynamics across different markets and sectors, underscoring the enduring nature of volatility and its response to specific events. Additionally, investigations by Marobhe and Pastory (2020) and Jafry, et al. (2022) provide insights into volatility patterns in markets beyond India, showcasing the global applicability of volatility modelling techniques.

Furthermore, research on volatility forecasting has expanded to include advanced techniques like wavelet transformed ARIMA and GARCH models, offering improved prediction accuracy even in non-linear time-series patterns. Studies by Rubio et al. (2023), Zolfaghari and Gholami (2021), Paul (2015), and Yao, et al. (2020) contribute to this ongoing exploration of forecasting methodologies.

2. Research Methodology

The current study takes into account daily closing price of sixteen sectoral indices. The historical data for closing daily prices has been taken from the NSE website (https://www.nseindia.com/reports-indices-historical-index-data, retrived on 2nd February 2024). Nifty Auto, Nifty Bank, Nifty Energy, Nifty Financial Services, Nifty FMCG, Nifty IT, Nifty Media, Nifty Metal, Nifty PSU Bank, Nifty Pvt Bank, Nifty Pharma and Nifty Realty indices are analysed for the period 01st January, 2019 to 31st January, 2024. However, the data for Nifty Oil and Gas, Nifty Healthcare, Nifty Consumer Durables was available for the period 9th August, 2021 to 31st January, 2024 and Nifty Financial Services 25/50 for the period 10th August, 2020 to 31st January, 2024.

Augmented Dicky-Fuller test has been applied to check for stationarity in the series of all indices. The stationarity of the series has been achieved by transforming the daily prices into differenced natural logarithm.
The regression analysis on the returns was conducted using ordinary least squares method (OLS). ARMA technique has been employed to identify Autoregressive (AR) and Moving Average (MA) terms.

The presence of conditional heteroskedasticity has been checked using Autoregressive Conditional Heteroskedasticity (ARCH) test. The computation of persistence of volatility and volatility decaying rate (VDR) has been done using GARCH for symmetric models and TGARCH for assymetric models. Finally, the mean equations of GARCH and TGARCH models have been used to forecast the future returns of the sectoral indices for the period beginning 1st February, 2024 until 30th April, 2024.

3. Results and Discussion

Daily closing prices of the indices are converted to returns after taking natural logarithm. Application of Augmented Dickey-Fuller Test yielded *p-value* of less than 0.05 confirming the stationarity of the natural logarithm return series. The descriptive statistics of the logarithm returns are given in Table 1.

Table 1: Descriptive Statistics of Log Returns of Nifty Sectoral Indices

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.	N*
Nifty Auto	0.0006	0.0157	-0.6136	14.56	7069.85	0.00	1256
Nifty Bank	0.0004	0.0166	-1.1892	19.93	15297.35	0.00	1256
Nifty Energy	0.0007	0.0141	-0.5447	10.00	2627.23	0.00	1256
Nifty Financial Services	0.0004	0.0158	-1.2942	20.01	15497.62	0.00	1256

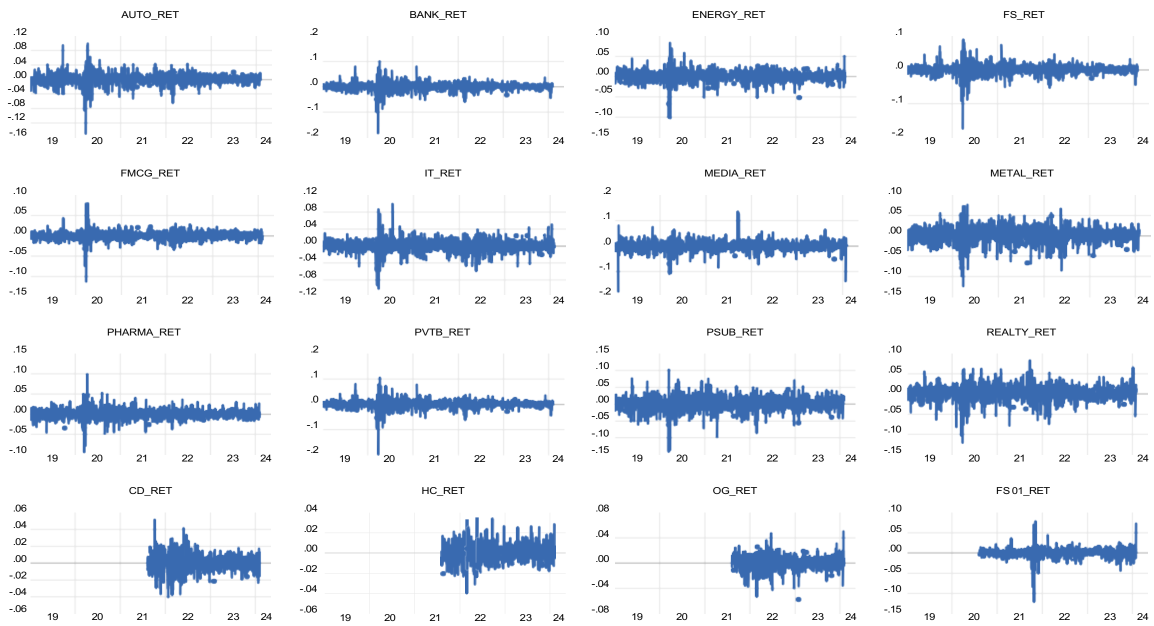
European Economic Letters
ISSN 2323-5233
Vol 13, Issue 3 (2023)
https://doi.org/10.52783/eel.v13i3.331
http://eelet.org.uk

Nifty FMCG	0.0005	0.0106	-0.5224	21.12	17248.23	0.00	1256
Nifty IT	0.0007	0.0148	-0.3252	10.49	2959.94	0.00	1256
Nifty Media	-0.0001	0.0203	-0.7347	13.62	6012.87	0.00	1256
Nifty Metal	0.0007	0.0196	-0.6452	6.48	721.35	0.00	1256
Nifty Pharma	0.0006	0.0126	-0.0140	10.60	3019.44	0.00	1256
Nifty Private Bank	0.0003	0.0170	-1.3352	22.54	20351.93	0.00	1256
Nifty PSU Bank	0.0006	0.0213	-0.4710	7.08	915.51	0.00	1256
Nifty Realty	0.0010	0.0190	-0.5701	7.08	939.79	0.00	1256
Nifty Consumer Durables	0.0004	0.0105	-0.2193	5.23	132.65	0.00	615
Nifty HealthCare	0.0004	0.0095	0.0819	3.98	25.21	0.00	615
Nifty Oil & Gas	0.0008	0.0119	-0.5757	5.73	224.67	0.00	615
Nifty Financial Services 25/50	0.0005	0.0123	-1.1407	22.29	13576.65	0.00	864

*Source: Authors own using Eviews 12 from NSE data. *: No. of Observatons*

The average return of Nifty Oil & Gas is highest, closely followed by Energy, Metal and IT. The Nifty Media Index shows negative return for the period under study. Nifty Healthcare has the lowest standard deviation while PSU banks has the highest. All the indices are negatively skewed except Nifty Healthcare. The kurtosis of all indices is greater than three, indicating the return series are leptokurtic or fat-tailed distribution. All indices are not normally distributed as the *p-value* < 0.05 of Jarque-Bera test.

Figure 1: Volatility Clustering of log returns of Nifty Indices



Source: Authors own using Eviews 12 from NSE data

Volatility clustering refers to the phenomenon where large changes tend to be followed by large changes and small changes by small (Mandelbrot, 1963). Figure 1 shows the volatility clustering of log returns for all sectoral indices of Nifty, signifying that volatility is persistent over time.

Table 2 shows the ARCH LM (Lagrange Mulltiplier) test. The *p-value* < 0.05 for all indices, indicating the presence of heteroskedasticity, which favour the employment of the GARCH model.

European Economic Letters
ISSN 2323-5233
Vol 13, Issue 3 (2023)
https://doi.org/10.52783/eel.v13i3.331
http://eelet.org.uk

Table 2: Results of Heteroskedasticity Test-- ARCH LM Test			
Indices	**F-statistic**	**Prob.**	**DF**
Nifty Auto	11.74105	0.0006	(1,1253)
Nifty Bank	50.87252	0.0000	(1,1253)
Nifty Energy	73.35455	0.0000	(1,1248)
Nifty Financial Services	130.75150	0.0000	(1,1250)
Nifty FMCG	13.54024	0.0000	(5,1239)
Nifty IT	42.46218	0.0000	(1,1248)
Nifty Media	29.63415	0.0000	(1,1246)
Nifty Metal	37.33389	0.0000	(1,1252)
Nifty Pharma	76.49944	0.0000	(1,1251)
Nifty Private Bank	52.97630	0.0000	(1,1248)
Nifty PSU Bank	48.84169	0.0000	(1,1253)
Nifty Realty	21.42848	0.0000	(1,1248)
Nifty Consumer Durables	8.00118	0.0004	(1,612)
Nifty HealthCare	10.40135	0.0013	(1,612)
Nifty Oil & Gas	10.71217	0.0000	(1, 611)
Nifty Financial Services 25/50	25.04109	0.0000	(1,856)

Source: Authors own using Eviews 12 from NSE data

Table 3 shows the results of the regression analysis on the return series using ordinary least squares method (OLS). Autoregressive (AR) and/or Moving Average (MA) components were introduced to make the model fit, where autocorrelation (ACF) or partial autocorrelation (PACF) in the residual series are significant. The mean equation thus obtained from this analysis is used for forecasting future returns of the indices under study.

Table 3:Results of Ordinary Least Square (Mean Equation)						
	GARCH			**TGARCH**		
Indices	**Constant (*p-value*)**	**AR (*p-value*)**	**MA (*p-value*)**	**Constant (*p-value*)**	**AR (*p-value*)**	**MA (*p-value*)**
Nifty Auto	0.001			0.0008		
	(0.0012)			(0.0078)		
Nifty Bank	**C**	**AR(4)**	**MA(5)**	**C**	**AR(4)**	**MA(5)**
	0.001	0.0317	0.0368	0.0007	0.0377	0.0424
	(0.0079)	(0.2545)	(0.1782)	(0.0334)	(0.1693)	(0.1202)
			MA(6)			**MA(6)**
			-0.0432			-0.0335
			(0.1138)			(0.2178)
Nifty Energy	**C**	**AR(2)**	**MA(5)**	**C**	**AR(2)**	**MA(5)**
	0.001	-0.0083	-0.9302	0.0010	-0.0061	-0.9293
	(0.0014)	(0.3146)	(0.0000)	(0.0079)	(0.4377)	(0.0000)
		AR(5)	**MA(6)**		**AR(5)**	**MA(6)**
		0.9421	-0.0062		0.9429	-0.0041
		(0.0000)	(0.4973)		(0.0000)	(0.6463)
Nifty Financial Services	**C**	**AR(3)**	**MA(3)**	**C**	**AR(3)**	**MA(3)**
	0.0009	0.3671	-0.4240	0.0008	0.3027	-0.3500

	(0.0005)	(0.1068)	(0.05680	(0.0035)	(0.1599)	(0.10130
Nifty FMCG	**C**	**AR(1)**		**C**	**AR(1)**	
	0.0006	0.0233		0.0005	0.0206	
	(0.0104)	(0.4103)		-0.023681	(0.4035)	
Nifty IT	**C**	**AR(5)**	**MA(6)**	**C**	**AR(5)**	**MA(6)**
	0.001	0.0124	-0.5764	0.0009	0.017001	-0.5630
	(0.003)	(0.568)	(0.004)	(0.0092)	(0.4312)	(0.0027)
		AR(6)			**AR(6)**	
		0.565362			0.5517	
		(0.005)			(0.0034)	
Nifty Media	**C**			**C**		
	0.0005			0.0003		
	(0.2659)			(0.4373)		
Nifty Metal	**C**			**C**		
	0.0016			0.0014		
	(0.0006)			(0.0029)		
Nifty Pharma	**C**			**C**		
	0.0005			0.0004		
	(0.0537)			(0.1806)		
Nifty Pvt Bank	**C**	**AR(5)**	**MA(1)**	**C**	**AR(5)**	**MA(1)**
	0.0007	0.0363	0.0692	0.0006	0.0430	0.0771
	(0.0187)	(0.1824)	(0.015)	(0.081)	(0.1126)	(0.0062)
			MA(6)			**MA(6)**
			-0.0494			-0.03966
			(0.0715)			(0.1452)
Nifty PSU Bank	**C**	**AR(5)**	**MA(5)**	**C**	**AR(5)**	**MA(5)**
	0.0009	-0.0042	0.0353	0.0008	-0.0049	0.0369
	(0.0957)	(0.9861)	(0.8847)	(0.1302)	(0.9836)	(0.8785)
Nifty Realty	**C**	**AR(5)**	**MA(1)**	**C**	**AR(5)**	**MA(1)**
	0.0016	0.0448	0.0903	0.0005	0.0488	0.0917
	(0.0013)	(0.1134)	(0.0012)	(0.0043)	(0.0855)	(0.0012)
Nifty Consumer Durables	**C**	**AR(1)**	**MA(1)**	**C**	**AR(1)**	**MA(1)**
	0.0009	-0.4368	0.5171	0.0003	-0.2652	0.3792
	(0.0125)	(0.2254)	(0.1301)	(0.4229)	(0.417)	(0.2223)
Nifty Healthcare	**C**			**C**		
	0.0005			0.0003		
	(0.1579)			(0.4229)		
Nifty Oil &Gas	**C**	**AR(1)**	**MA(1)**	**C**	**AR(1)**	**MA(1)**
	0.0012	0.9391	-0.9215	0.0012	0.9234	-0.8967
	(0.0206)	(0.000)	(0.000)	(0.0337)	(0.000)	(0.000)
Nifty FS 25/50	**C**	**AR(4)**	**MA(1)**	**C**	**AR(4)**	**MA(1)**
	0.0575	0.0587	0.0891	0.0478	0.0555	0.1080
	(0.0017)	(0.0785)	(0.006)	(0.0093)	(0.0962)	(0.0009)

Source: Authors own using Eviews 12 from NSE data

Table 4 provides the estimated parameters of GARCH model for Nifty sectoral indices. All parameters ω, α and $\beta \geq 0$ and $\alpha + \beta \leq 1$, satisfy the stability conditions of GARCH model, signifying GARCH (1,1) as the model of best fit. However, for Nifty PSU Bank, the GARCH (1,2) is the model of best fit and therefore, has been discussed separately.

European Economic Letters
ISSN 2323-5233
Vol 13, Issue 3 (2023)
https://doi.org/10.52783/eel.v13i3.331
http://eelet.org.uk

Table 4: Parameters of Variance Equation (GARCH) and Volatility Decaying Effect					
Indices	**Parameters**			**Volatility Persistence**	**VDR(%)**
	ω *(p-value)*	**α** *(p-value)*	**β** *(p-value)*	**α+β ≤ 1**	
Nifty Auto	0.00000549	0.087976	0.889307	0.977283	2.27
	(0.0077)	(0.000)	(0.000)		
Nifty Bank	0.00000309	0.084708	0.905551	0.990259	0.97
	0.0095	(0.000)	(0.000)		
Nifty Energy	0.00000889	0.104987	0.847135	0.952122	4.79
	(0.005)	(0.000)	(0.000)		
Nifty Financial Services	0.00000299	0.083926	0.904499	0.988425	1.16
	(0.010)	(0.000)	(0.000)		
Nifty FMCG	0.00000395	0.07942	0.874774	0.954194	4.58
	(0.0072)	(0.0001)	(0.000)		
Nifty IT	0.0000075	0.06193	0.902555	0.964485	3.55
	(0.008)	(0.000)	(0.000)		
Nifty Media	0.0000487	0.173899	0.697676	0.871575	12.84
	(0.0016)	(0.0001)	(0.000)		
Nifty Metal	0.00000798	0.066078	0.914535	0.980613	1.94
	(0.0344)	(0.000)	(0.000)		
Nifty Pharma	0.00000487	0.081411	0.885283	0.966694	3.33
	(0.0063)	(0.000)	(0.000)		
Nifty Private Bank	0.00000331	0.086921	0.90244	0.989361	1.06
	(0.009)	(0.000)	(0.000)		
Nifty Realty	0.00000843	0.05875	0.918292	0.977042	2.30
	(0.01680)	(0.0001)	(0.000)		
Nifty Consumer Durables	0.00000181	0.064986	0.920039	0.985025	1.50
	(0.087)	(0.005)	(0.000)		
Nifty Health Care	0.000001	0.026249	0.965748	0.991997	0.80
	(0.325)	(0.045)	(0.000)		
Nifty Oil & Gas	0.0000048	0.07411	0.897362	0.971472	2.85
	(0.072)	(0.0099)	(0.000)		
Nifty Financial services 25/50	0.00000201	0.067045	0.919558	0.986603	1.34
	(0.0868)	(0.0008)	(0.000)		

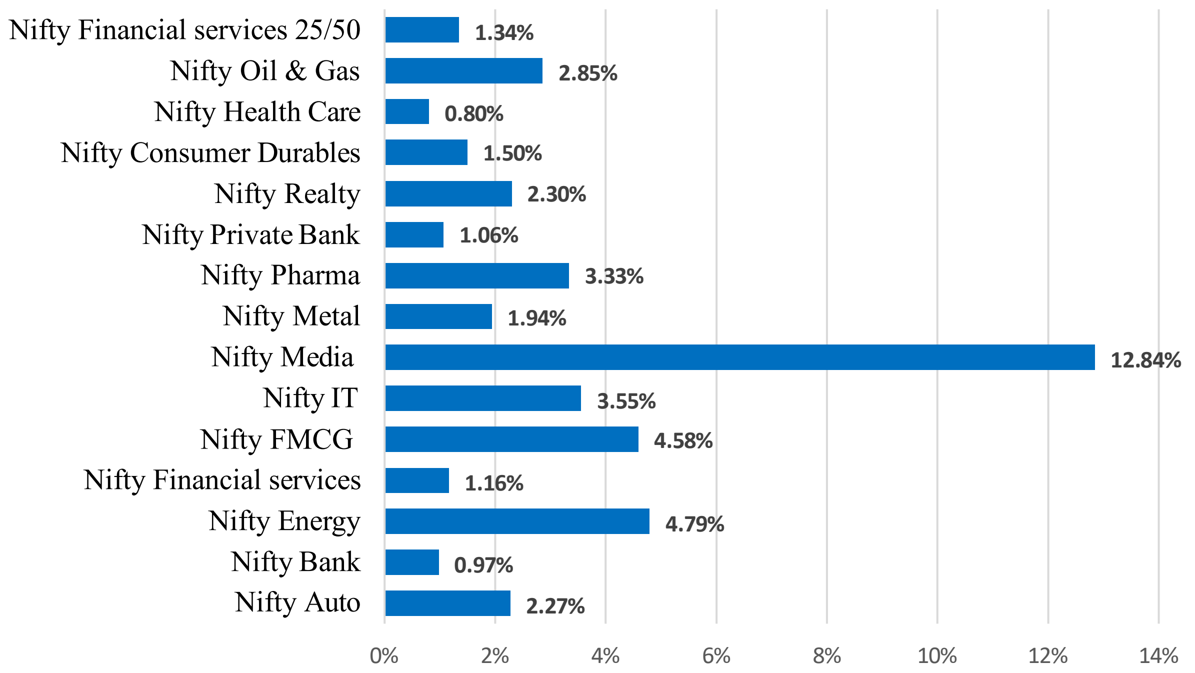
Source: Authors own using Eviews 12 from NSE data

In Table 4, the *p-value(s)* of α and β are significant for all indices indicating the time varying behaviour of volatility and there exists high volatility persistence in the return series as $\alpha+\beta$ close to 1. Additionally, Table 4 illustrates the rate at which volatility declines, with Nifty Media showing the highest rate and Nifty Healthcare the lowest. This rate signifies, how quickly the volatility dissipates in the market. Risk-averse investors may favour stocks with the highest decay rate, whereas agressive investors may prefer the opposite.

Figure 2 gives the graphical representation of VDR, whereby, it is evident that Nifty Media has the highest VDR at 12.84 per cent followed by Nifty Energy, which has a VDR of 4.79 per cent. The difference between the top two indices is significant whereby, Nifty Media is way ahead of other indices. The lowest VDR is of Nifty Healthcare at 0.80.

European Economic Letters
ISSN 2323-5233
Vol 13, Issue 3 (2023)
https://doi.org/10.52783/eel.v13i3.331
http://eelet.org.uk

Figure 2: Volatility Decaying Rate using GARCH Model



Source: Authors own

Table 5 shows the estimated parameters of TGARCH model, where γ represents the presence of leverage effect in the stock-market. The impact of news for all sectoral indicates is greater than zero ($\gamma > 0$) and significant at 1 per cent level for Nifty Auto, Nifty Bank, Nifty Energy, Nifty Financial Services, Nifty IT, Nifty Metal, Nifty Pharma, Nifty Pvt Bank, Nifty Consumer Durables, Nifty Healthcare and Nifty Financial Services 25/50; significant at 5 per cent for Nifty Realty and Nifty Oil & Gas; and significant at 10 per cent for Nifty FMCG and Nifty Media. The result signifies that negative shocks will exert greater influene on conditional variance compared to positive shocks.
Nifty Media has the highest VDR of 18.92 per cent, followed by Nifty Energy 14.31 per cent. Nifty Bank has lowest VDR of 5.82 per cent.

Table 5: Parameters of Variance Equation (TGARCH) and Volatility Decaying Effect

Indices	Parameters			News Impact	Volatility Persistence	VDR (%)
	ω *(p-value)*	α *(p-value)*	β *(p-value)*	γ *(p-value)*	α+β ≤ 1	
Nifty Auto	0.000005	0.02527	0.90434	0.093365	--	--
	(0.002)	(0.139)	(0.000)	(0.000)***		
Nifty Bank	0.000002	0.029182	0.91265	0.091797	0.9418	5.82
	(0.005)	(0.070)*	(0.000)	(0.000)***		
Nifty Energy	0.000014	0.057476	0.79944	0.11877	0.8569	14.31
	(0.000)	(0.064)*	(0.000)	(0.004)***		
Nifty Financial services	0.000003	0.022546	0.918	0.093973	--	--
	(0.0065)	(0.1262)	(0.000)	(0.0001)***		
Nifty FMCG	0.000003	0.04444	0.88966	0.04926	0.9341	6.59
	(0.0065)	(0.014)**	(0.000)	(0.0938)*		
Nifty IT	0.000009	0.014787	0.89705	0.088012	--	--
	(0.002)	(0.316)	(0.000)	(0.002)***		
Nifty Media	0.000049	0.109609	0.70117	0.111256	0.8108	18.92

European Economic Letters
ISSN 2323-5233
Vol 13, Issue 3 (2023)
https://doi.org/10.52783/eel.v13i3.331
http://eelet.org.uk

	(0.0011)	(0.013)**	(0.000)	(0.059)*		
Nifty Metal	0.000008	0.023806	0.91953	0.06386	--	--
	(0.0124)	(0.198)	(0.000)	(0.005)***		
Nifty Pharma	0.000004	0.024498	0.90157	0.093216	--	--
	(0.0043)	(0.1062)	(0.000)	(0.001)***		
Nifty Private Bank	0.000322	0.032149	0.90675	0.0953	0.9389	6.11
	(0.005)	(0.075)*	(0.000)	(0.000)***		
Nifty Realty	0.000014	0.033657	0.89067	0.072399	0.9243	7.57
	(0.005)	(0.0556)*	(0.000)	(0.0183)**		
Nifty Consumer Durable	0.000006	0.036034	0.83787	0.145324	--	--
	(0.006)	(0.230)	(0.000)	(0.006)***		
Nifty Healthcare	0.00001	-0.05288	0.83588	0.218683	Model cannot be fitted	
	(0.002)	(0.048)	(0.000)	(0.002)***		
Nifty Oil & Gas	0.000019	0.038396	0.73837	0.168557	--	--
	(0.0095)	(0.4976)	(0.000)	(0.0273)**		
Nifty Financial Services 25/50	0.000002	0.007524	0.92435	0.096691	--	--
	(0.0304)	(0.696)	(0.000)	(0.001)***		

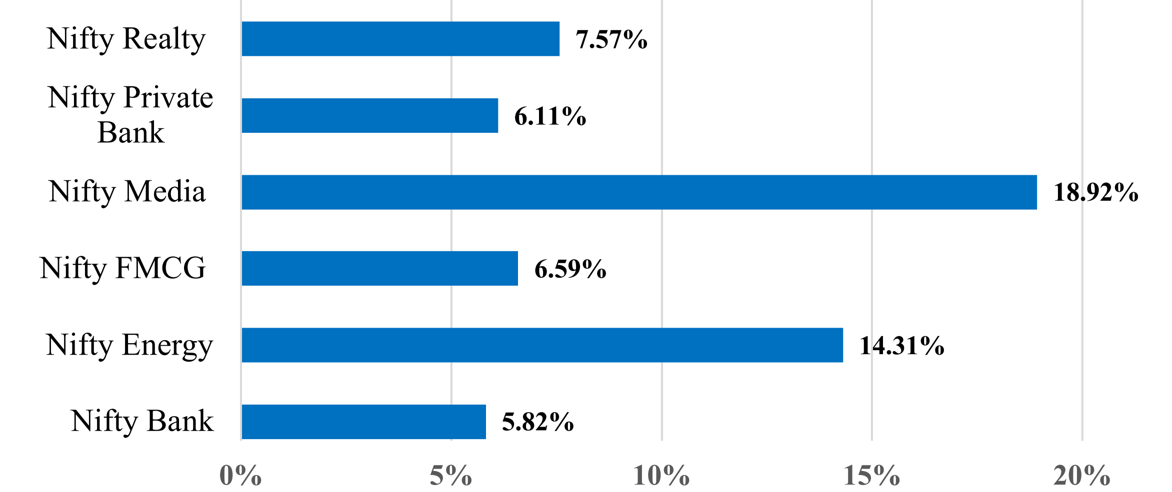
Source: Authors own using Eviews 12 from NSE data

The impact of news is significant for Nifty Auto, Nifty Financial Services, Nifty IT, Nifty Metal, Nifty Pharma, Nifty Consumer Durables, Nifty Oil & Gas and Nifty Financial Services 25/50, due to the presence of leverage effect, yet TGARCH model is unable to capture it, as the *p-values* of the coefficients of $\alpha > 0.05$. As a result, the VDR cannot be calculated.

However, α for Nifty Healthcare is negative, denoting that the stability condition of parameters for TGARCH model are not fulfilled. Therefore, TGARCH model cannot be applied to Nifty Healthcare.

Figure 3 represents the VDR of TGARCH Model. Again, Nifty Media has the highest VDR of 18.92 per cent followed by Nifty Energy at 14.31 per cent. The lowest VDR in TGARCH model is of Nifty Bank at 5.82 per cent.

Figure 3: Volatility Decaying Rate using TGARCH Model



Source: Authors own

Table 6 discusses the GARCH and TGARCH models for Nifty PSU Bank. GARCH (1,2) and TGARCH (1,2) are the models of best fit. For GARCH (1,2), $\alpha+\beta_1 = 0.763 < 1$, indicating a VDR of 23.66%.

European Economic Letters
ISSN 2323-5233
Vol 13, Issue 3 (2023)
https://doi.org/10.52783/eel.v13i3.331
http://eelet.org.uk

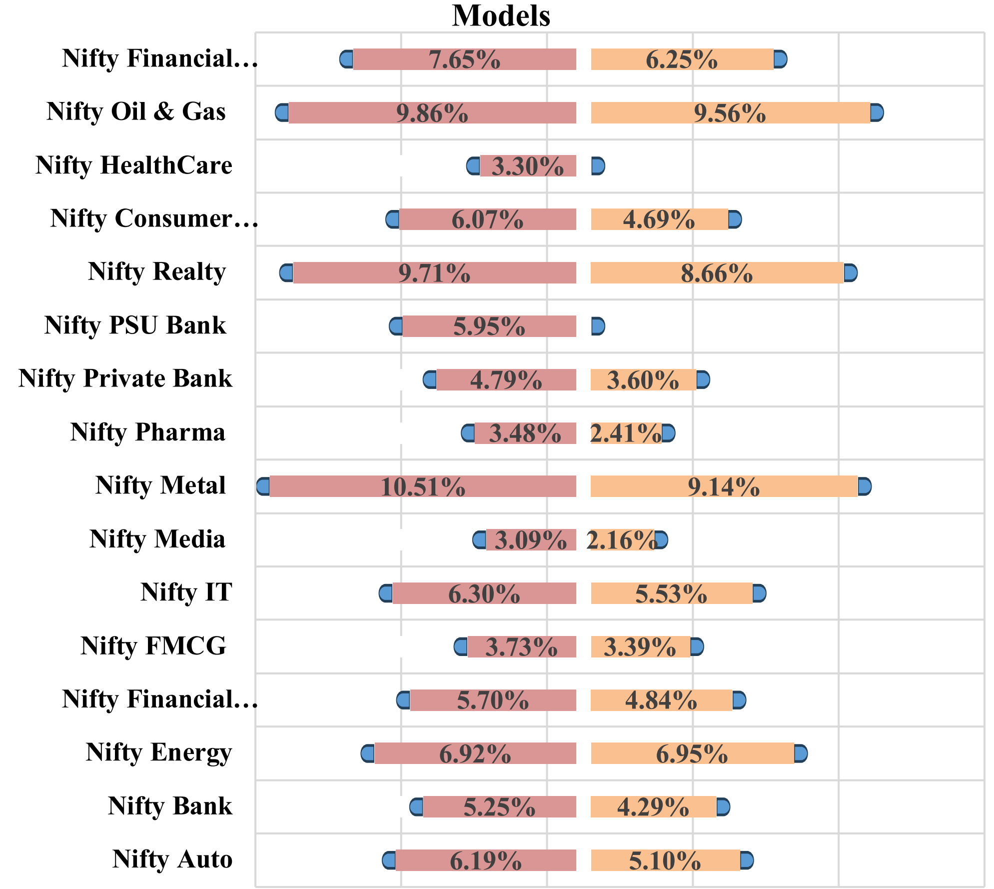
Table 6: Nifty PSU Bank GARCH(1,2) TGARCH(1,2)

	ω *(p-value)*	α *(p-value)*	β *(p-value)*	β_1 *(p-value)*		Volatility Persistence	VDR (%)
GARCH (1,2)	0.00002	0.0856	0.181	0.6778		0.763	23.66
	(0.013)	(0.0002)***	(0.35)	(0.0003)***			
	ω *(p-value)*	α *(p-value)*	β *(p-value)*	β_1 *(p-value)*	γ *(p-value)*		
TGARCH (1,2)	0.00002	0.0568	0.154	0.0495	0.7081	--	--
	(0.008)	(0.032)**	(0.34)	(0.124)	(0.0)***		

Source: Authors own using Eviews 12 from NSE data

In TGARCH (1,2) model, β and β_1 are insignificant, as their p-value > 0.05. The long run variance or persistence of volatility is absent. Hence, asymmetric model is not suitable for capturing the impact of News for Nifty PSU Bank. In Figure 4 the forecasted returns of all stock indices using GARCH and TGARCH model for the period 1st February, 2024 until 30th April, 2024 are shown.

Figure 4: Forecasted Returns using GARCH & TGARCH Models



Source: Authors own

The returns for the forecasted period are lower in TGARCH than in GARCH, highlighting the asymmetry's impact, except for NIFTY Energy where returns are nearly identical in both the models.
In the GARCH model, the highest return is forecasted for Nifty Metal at 10.51 per cent and volatility decay rate of 1.94 per cent. Likewise, for Nifty Oil & Gas has decaying rate of 2.85 per cent and forecasted return of 9.86 per cent. For Nifty Bank, where volatility decay rate is 23.66 per cent and has a return of 5.95 per cent. For Nifty Realty the forecasted returns are 9.71 per cent and volatility decay rate of 2.3 per cent.

In the TGARCH model, the highest VDR of 18.92 per cent is seen for Nifty Media with a forecasted return of 2.16 per cent, closely followed by Nifty Bank with a VDR of 14.31 per cent and the forecasted return of 4.29 per cent. The highest return on investment of 9.56% is in Nifty Oil & Gas, followed by Nifty Metal at 9.14 per cent, however VDR for these two indices cannot be determined. The return on investment of Nifty Realty is 8.66 per cent with a VDR of 7.57 per cent. The lowest decay rate is in Nifty Auto with a forecasted return of 5.10 per cent.

4. Conclusion

The study finds that in the GARCH model, indices with VDR ≥ 10, the returns for investors lie in the range of 3.09 percent and 5.95 percent. When the VDR < 10, in that case, the returns lie in the range of 3.30 per cent and 10.51 per cent.

When analysing the TGARCH model, indices with VDR ≥ 10, the returns for investors lie in the range of 2.16 percent and 4.29 percent. When the VDR < 10, in that case, the returns lie in the range of 3.60 per cent and 8.66 per cent.
The returns tend to be higher, when the VDR < 10, in both the symmetric and asymmetric models.
Stock-market indices exhibit asymmetry, meaning that when negative news impacts the financial market, assets tend to become turbulent, leading to increased volatility. A risk-averse investor can mitigate the risk (volatility) by investing in stocks/indices with the highest decay rate and be content with lower returns.
The relationship between volatility decay rate and forecasted return is inversely correlated. The higher the volatility decay rate, lower will be the forecasted return.

Recommendations for future research: The current study has looked into sixteen sectoral indices though, the same methodology can be applied to individual stocks of listed companies in order to analyse the impact of news on returns of selected corporates.
The study found that TGARCH could not capture the effect of news on certain indices. This opens up avenues for further exploration of such indices by employing other asymmetric models of GARCH family such as EGARCH and IGARCH.

References

1. Adesina, K. S. (2013). Modelling Stock Market Return Volatility: GARCH Evidence from Nigerian Stock Exchange. *International Journal of Financial Management*, 3(3), 37-46.
2. Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating Stock Market Volatility using Asymmetric GARCH Models. *Applied Financial Economics*. 18, 1201-1208
3. Anoop, P., Parab, N., & Reddy, Y. V. (2018). Analyzing the Impact of Demonetization on the Indian Stock Market: Sectoral Evidence using the GARCH Model. *Australasian Accounting, Business and Finance Journal*, 12(2), 104–116.
4. Arora, S., & Dang, K. (2019). Modelling Volatility in Future and Spot Returns. *Journal of Global Information and Business Strategy*. 11(1), 37-43
5. Awalludin, S. A., Ulfah, S., & Soro, S. (2018). Modeling the stock price returns volatility using GARCH (1, 1) in some Indonesia stock prices. In *Journal of Physics: Conference Series* (Vol. 948, No. 1, p. 012068). IOP Publishing.
6. Bhatia, P., & Gupta, P. (2020). Sub-prime crisis or COVID-19: A comparative analysis of volatility in Indian banking sectoral indices. *FIIB Business Review*, *9*(4), 286-299.
7. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327
8. Chang, C. L., McAleer, M., & Tansuchat, R. (2012). Modelling long memory volatility in agricultural commodity futures returns. *Annals of Financial Economics*, *7*(02), 1250010.
9. Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric eviews*, *5*(1), 1-50.
10. Engle, R.F., Lilien, D. M., & Robbins, R. P. (1987). Estimating Time Varying Risk Premia in the Term Structure: the ARCH-M Model, *Econometrica* 55, 391-408
11. Glosten, L R., Jagannathan, R., & Runkle, D. E. (1993) On the relation between expected value and the volatility of the nominal excess return on stocks, *Journal of Finance*, 48, 1779–1801.

12. Karmakar, M. (2005). Modeling Conditional Volatility of the Indian Stock Market. *Vikalpa: The Journal for Decision Makers*, 30(3). https://doi.org/10.1177/0256090920050303
13. Karmakar, M. (2007). Asymmetric volatility and risk-return relationship in the Indian stock market. *South Asia Economics Journal*,8(1), 99-116. https://doi.org/10.1177/139156140600800106
14. Idrees, S.M., Alam, M.A., & Agarwal, P. (2019). A prediction approach for stock market volatility based on time series data. *IEEE Access*. 17287-17298.
15. Jafry, N.H.A, Ab Razak, R., & Ismail, M. (2022). Modelling Malaysia stock market using GARCH, EGARCH, and Couple Models. *Journal of Optimization in Industrial Engineering*. 15(2), 295-303.
16. Khera, A., Goyal, A., & Yadav, M. P. (2022). Capturing the stock market volatility: a study of sectoral indices in India using symmetric GARCH models. *International Journal of Management Practice*, *15*(6), 820-833.
17. Malik, F., & Hassan, S. A. (2004). Modeling volatility in sector index returns with GARCH models using an iterated algorithm. *Journal of Economics and Finance*, *28*(2), 211-225.
18. Mallikarjuna, M., & Rao, R. P. (2017). Volatility behaviour in selected sectoral indices of Indian stock arkets. *Asian Journal of Research in Banking and Finance*, *7*(2), 23-34.
19. Mandelbrot, B. B. (1963). The Variation of Certain Speculative Prices. *Journal of Business* 36, 394-419
20. Marobhe, M., & Pastory, D. (2020). Modeling Stock Market Volatility Using GARCH Models Case Study of Dar es Salaam Stock Exchange (DSE). Review of Integrative Business and Economics Research, Vol. 9, Issue 2.
21. Marreh, S., Olubusoye, O.E., & Kihoro, J.M. (2014). Modeling volatility in the Gambian exchange rates: An ARMA-GARCH Approch. *International Journal of Economics and Finance*. 6(10); 118-128
22. Meher, B. K., Hawaldar, I. T., Thomas Gil, M., & Dum, Z. (2021). Measuring leverage effect of covid-19 on stock price volatility of energy companies using high frequency data. International Journal of Energy Economics and Policy, 11(6), 489-502.
23. Mittal, A.K., & Goyal, N. (2012), "Modeling the volatility of Indian stock market", *International Journal of Research in IT & Management*, Vol. 2 No. 1, pp. 1-23.
24. Mukherjee, I., & Goswami, B. (2017). The volatility of returns from commodity futures: Evidence from India. *Financial Innovation*, *3*, 1-23.
25. Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society*, 347-370.
26. Nikhil, M.N., Chakraborty, S., Lithin, B.M., Sanket, L., & Satyakam (2023). Modeling Indian bank Nifty volatility using univariate GARCH models. *Banks and Banks System*, 18(1), 127-138. Doi: 10.21522/bbs. 18(1).2023.11
27. Onali, E. (2020). Covid-19 and stock market volatility. *Available at SSRN*
28. *3571453*: https://ssrn.com/abstract=3571453.
29. Padhi, P. (2006). Persistence and asymmetric volatility in Indian stock market. *Journal of Quantitative Economics*, 4, 103-113.https://doi.org/10.1007/BF03546451
30. Paul, R. K. (2015). ARIMAX-GARCH-WAVELET model for forecasting volatile data. *Model Assisted Statistics and Applications*, 10(3), 243-252.
31. Rubio, L., Palacio Pinedo, A., Mejía Castaño, A., & Ramos, F. (2023). Forecasting volatility by using wavelet transform, ARIMA and GARCH models. *Eurasian Economic Review*, 1-28.
32. Sen, J., Mehtab, S., & Dutta, A. (2021). Volatility Modeling of Stocks from Selected Sectors of the Indian Economy Using GARCH. 2021 Asian Conference on Innovation in Technology (ASIANCON). https://doi.org/10.1109/asiancon51346.2021.9544977.
33. Tabassum, S., Yadav, M. P., Yadav, S., & Al-Qudah, A. A. (2023). Capturing Symmetrical and Asymmetrical Volatility in the Energy Market: Evidence of COVID-19 Outbreak and Russia Ukraine Saga. *FIIB Business Review*, 23197145231176113.
34. Vasudevan, R. D., & Vetrivel, S. C. (2016). Forecasting stock market volatility using GARCH models: Evidence from the Indian stock market. *Asian Journal of Research in Social Sciences and Humanities*, *6*(8), 1565-1574.
35. Wang, Y., Xiang, Y., Lei, X., & Zhou, Y. (2022). Volatility analysis based on GARCH-type models: Evidence from the Chinese stock market. *Economic research-Ekonomska istraživanja*, 35(1), 2530-2554.
36. Yao, R., Zhang, W., & Zhang, L. (2020). Hybrid methods for short-term traffic flow prediction based on ARIMA-GARCH model and wavelet neural network. *Journal of Transportation Engineering, Part A: Systems*, *146*(8), 04020086.
37. Zolfaghari, M. & Gholami, S. (2021). A hybrid approach of adaptive wavelet transform, long short-term memory and ARIMA-GARCH family models for the stock index prediction. *Expert Systems with Applications*, *182*, 115149