Application Of Conditional Heteroscadicity Model On Sectoral Index In India With Special Reference To Banking Sector Using Garch Model

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Abstract:

The objective of this paper is to investigate the impact of volatility in stock prices of banking sector. The sample data consist of closing prices of Bank Nifty from January 1, 2017 to December 31, 2019. The study uses EGARCH model tocapture volatility clustering, persistence and leverage effect.The result shows ARCH Effect (C3) is positive i.e. there is a positive relation between the past variance and the current variance in absolute value,Leverage effect (C4) is negative indicates an asymmetric effect i.e. Bad news will increase volatility more than a good new of the same size and Significant and positive value of GARCH Term (C5) indicates present volatility or conditional variance is significantly affected by previous period conditional variance.

INTRODUCTION

The volatility in the returns of financial time-series is a main focus of attention among researchers, investors, portfolio managers, and other market practitioners. The reason is that volatility is used as a proxy for risk or uncertainty. Volatility was first applied by Markowitz (1952) as a measure of risk in portfolio selection. Accurate forecasts for the standard deviation or the variance of returns has become indispensable since it is a critical parameter in asset allocation in portfolio management, hedging, options pricing, and the calculation of value-at-risk (VaR). The volatility in the returns of financial time-series is characterized by stylized features commonly exhibited in most financial time-series in varying degrees. These stylized facts are volatility clustering, long memory, leptokurtosis and the leverage effect.

Volatility clustering also referred to as pooling implies that the variance is time-varying (heteroskedastic). Volatility clustering describes the tendency of large changes in asset prices to follow large changes and small changes to follow small changes.Long memory refers to the long-term dependencies or the persistence of autocorrelation in the volatility of financial time-series. Leptokurtosis refers to the heavy (fat) tails of the volatility indicating a non-normal distribution. The leverage effect refers to the negative correlation between volatility and asset returns (Black 1976). Among the various methods by which the variance can be estimated, the ARCH model introduced by Engle (1982) to specifically model and forecast conditional variances and the GARCH model introduced by Bollerslev (1986) have become the standard tools for variance modelling. These models are able to capture the stylized features of volatility persistence, volatility clustering and leptokurtosis, but not the asymmetric feature described as the leverage effect. The exponential GARCH or EGARCH introduced by Nelson (1991) and the threshold GARCH or TGARCH introduced by Zakoian (1994) can capture the leverage effect stylized fact where positive and negative shocks have asymmetric effects with negative shocks having a greater impact on volatility than positive shocks. This paper is an attempt to model conditional volatility of banking sector of National Stock Exchange of India i.e. BANK NIFTY by capturing volatility clustering, persistence and leverage effect.

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LITERATURE REVIEW

Krishna Murarihas model and forecasted the short-term volatility of the Indian banking sector.Data have been collected since January 2000 up to the period of June 2013.As per the analysis, ARIMA (1,0,2) model was found to be the best fit to forecast the volatility of bank sector stock returns.

William Coffie has and evaluates the performance of asymmetric first order generalised autoregressive conditional heteroscedasticity (GARCH 1, 1) models for Ghana and Nigeriastock market return. Data is collected from 1996-2013. Glosten Jagannathan and Runkle (GJR) version of GARCH (GJR-GARCH) and Exponential GARCH (EGARCH) methodology used to investigate the leverage effect of return volatility in Ghana and Nigeria stock markets using Gaussian, Student-t and Generalised Error Distribution (GED) densities.The EGARCH provides the best out-of-sample forecast for the Ghanaian stock market, while the GJR gives a better estimation for the Nigerian stock market.

Amanjot singhattempts to capture conditional variance of Indian banking sector's stock market returns across the years 2005 to 2015 by employing different GARCH based symmetric and asymmetric models.The exponential GARCH (EGARCH) model is found to be the best fit model capturing time-varying variance in the banking sector.The results report existence of persistency as well as leverage effects in the banking sector return volatility.On an expected note, the global financial crisis increased conditional volatility in the Indian banking sector during the years 2007 to 2009.

Dr. Shveta Singh, Teena has model the conditional volatility of banking sectors of National Stock Exchange, India and to capture its dynamics as volatility clustering, persistence and leverage effect.Data is collected from 1stApril 2011 to 31st March 2017.Volatility is analysed by applying EGARCH model on daily returns data of two sectors namely composite Bank sector (Bank) and PSU Bank sector (PSU).It is found that both sectors are showing volatility clustering, significant persistence and leverage effect but PSU bank sector is more prone to negative news and its returns are more volatile, composite Bank sector is less prone to negative shocks due to inclusion of private banks.

OBJECTIVE OF THE STUDY

- To model conditional volatility of banking sector of National Stock Exchange of India.
- To capture volatility clustering, persistence and leverage effect.

DATA SOURCE AND METHODOLOGY

Data is in form of daily closing prices of bank nifty has been taken from NSE website from 1st Jan 2017 to 31 Dec 2019. Logged returns have been obtained from daily closing prices to use in models.

$$\text{Return Series} = \text{Log}\ (Pt/Pt\text{-}1) * 100$$

Descriptive statistics: This is used to find the distribution of returns.

Test of stationarily

1. ADF test: Augmented dickey fuller test is used to find the stationarity of return series.

H0 = y series contains unit root or non-stationary.

H1= y series is stationary.

2. ARIMA (p, d, q) Modelling Process: where p denotes the no. of autoregressive terms, d the no. times the series has to be differenced before it becomes stationary and q the no. of moving average terms.

Residuals are checked for auto correlation

1) by using Ljung box Q statistics

H0: no autocorrelation among residuals.
H1: autocorrelation among residuals.

2) ARCH effect: to ascertain the presence of serial correlation in the residuals.

H0: no ARCH Effect in residuals.
H1: ARCH Effect in residuals.

Model testing: EGARCH MODEL

Diagnostic Test for The Best Fitted EGARCH Model:

1. ARCH Effect
2. using Ljung box Q statistics

DATA ANALYSIS

Descriptive statistics

Table 1 it can be seen that bank sector returns are positive during the study period. The Bank sector positive returns may be due to Private or public sectors stocks contribution. Standard deviation is low which lead to less risk and volatility. Sectors is positively skewed and kurtosis is excess of 3 indicating more peak values of returns means large fluctuations are happening within fat tails. Jarque Bera values is high and its p-values are less than 0.05 indicating returns are deviated from normal distribution.

Table 1:

	LN_RETUR...
Mean	0.000791
Median	0.000915
Maximum	0.079839
Minimum	-0.028678
Std. Dev.	0.010158
Skewness	0.878407
Kurtosis	9.339297
Jarque-Bera	1318.026
Probability	0.000000
Sum	0.578427
Sum Sq. Dev.	0.075326
Observations	731

ADF unit root test

In Table 3 ADF test results are shown it can be seen that bank sectors returns are stationary at levels with constant and trend. **H0** = series contains unit root or non-stationary. **H1**= series is stationary. The series should be stationary to apply EGARCH model.

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + u_t$$

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-25.66932	0.0000
Test critical values:	1% level	-3.970673	
	5% level	-3.415984	
	10% level	-3.130267	

*MacKinnon (1996) one-sided p-values.

Result: Bank sectors absolute t-statistics is greater than MacKinnon critical values. So, the **H0** of unit root or non-stationary series get rejected resulting series is stationary.

Modelling of ARIMA equation

Many time series data which are not stationary are integrated. Therefore, if we have to difference a time series d times to make it stationary.

Table 3:

ARMA TABLE

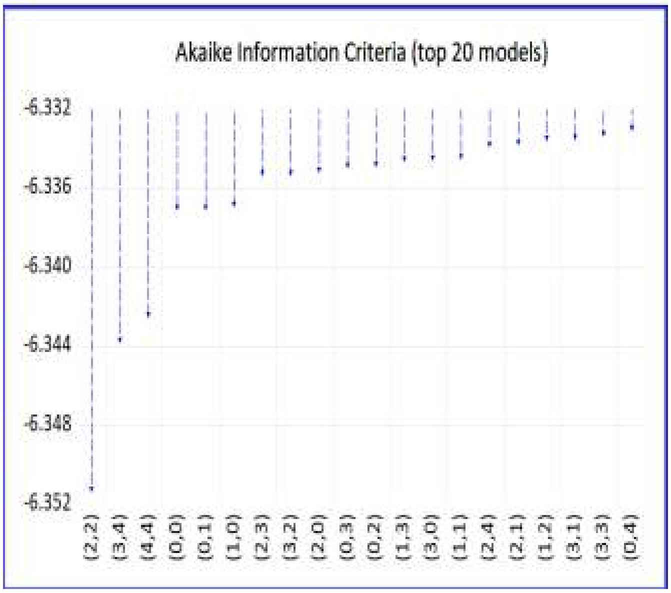
ARMA Criteria Table

Model Selection Criteria Table
Dependent Variable: LN_RETURNS
Date: 05/08/20 Time: 21:03
Sample: 1 731
Included observations: 731

Model	LogL	AIC*	BIC	HQ
(2,2)	2327.386852	-6.351264	-6.313553	-6.336715
(3,4)	2327.612476	-6.343673	-6.287107	-6.321851
(4,4)	2328.158749	-6.342432	-6.279581	-6.318186
(0,0)	2318.171831	-6.336085	-6.324425	-6.332146
(0,1)	2319.166981	-6.336062	-6.318127	-6.329708
(1,0)	2319.111534	-6.336030	-6.317975	-6.329656
(2,3)	2322.528836	-6.335236	-6.291240	-6.318263
(3,2)	2322.527894	-6.335234	-6.291238	-6.318261
(2,0)	2319.480639	-6.335104	-6.308964	-6.325406
(0,3)	2320.383150	-6.334838	-6.303412	-6.322714
(0,2)	2319.367633	-6.334795	-6.309655	-6.325096
(1,3)	2321.261183	-6.334504	-6.296793	-6.319956
(3,0)	2320.238896	-6.334446	-6.303020	-6.322322
(1,1)	2319.232763	-6.334426	-6.309286	-6.324727
(2,4)	2323.002256	-6.333796	-6.283515	-6.314398
(2,1)	2319.965675	-6.333695	-6.302270	-6.321572
(1,2)	2319.889705	-6.333488	-6.302062	-6.321364
(3,1)	2320.862666	-6.333414	-6.295703	-6.318865
(3,3)	2322.797599	-6.333236	-6.282955	-6.313838
(0,4)	2320.707590	-6.332989	-6.295279	-6.318441
(4,3)	2323.588627	-6.332864	-6.276098	-6.310842
(4,0)	2320.400287	-6.332149	-6.294438	-6.317600
(1,4)	2321.381686	-6.332125	-6.288129	-6.315152
(4,1)	2320.921345	-6.330838	-6.286842	-6.313865
(4,2)	2320.898846	-6.328043	-6.277762	-6.308646

ARMA GRAPH

ARMA Criteria Graph



Result: The ARIMA (2,0,2) model has been identified using the information criterion and log likelihood. As a user of these information criteria for a model selection guide, the model with the smallest information criterion (AIC) is selected with highest log livelihood.

TESTING RESIDUAL AUTOCORRELATION

Residuals are checked for auto correlation by using Ljung box Q statistics. Autocorrelation has been checked up to 36 lags. Table 3 is showing residuals diagnostics.

Table 4:

	AC	PAC	Q-Stat	Prob
1	0.051	0.051	1.8842	0.170
2	-0.029	-0.032	2.5042	0.286
3	-0.048	-0.045	4.2278	0.238
4	0.017	0.021	4.4333	0.351
5	-0.050	-0.055	6.2565	0.282
6	0.030	0.035	6.9337	0.327
7	0.007	0.002	6.9716	0.432
8	-0.085	-0.090	12.352	0.136
9	0.040	0.056	13.552	0.139
10	0.065	0.052	16.715	0.081
11	0.046	0.038	18.322	0.074
12	-0.014	-0.007	18.470	0.102
13	-0.025	-0.029	18.943	0.125
14	-0.076	-0.063	23.279	0.056
15	-0.044	-0.037	24.699	0.054
16	0.087	0.081	30.377	0.016
17	0.009	-0.004	30.431	0.023
18	0.063	0.074	33.372	0.015
19	-0.007	-0.008	33.408	0.022
20	-0.023	-0.034	33.793	0.028
21	-0.030	-0.017	34.479	0.032
22	0.064	0.048	37.527	0.021
23	-0.026	-0.026	38.022	0.025
24	0.003	0.032	38.027	0.034
25	-0.058	-0.059	40.621	0.025
26	-0.003	-0.000	40.627	0.034
27	0.066	0.059	43.983	0.021
28	0.022	-0.013	44.348	0.026
29	-0.037	-0.039	45.400	0.027
30	-0.017	0.014	45.627	0.034
31	0.057	0.062	48.103	0.026
32	-0.037	-0.041	49.143	0.027
33	-0.004	-0.006	49.154	0.035
34	-0.047	-0.062	50.861	0.032
35	-0.081	-0.072	55.891	0.014
36	-0.023	-0.000	56.287	0.017

Result: We can see that there is autocorrelation in residuals of bank sectors because p>0.05 for up to 15 lags. But after lag 15 to 36 at 5% level in Bank sector there is no autocorrelation. Hence, our null hypothesis of no autocorrelation gets rejected and alternative of autocorrelation among residuals gets accepted.

LM ARCH Effect

After this ARCH effect is checked up to lag two.We test for ARCH effects in the estimated mean equation to ascertain the presence of serial correlation in the residuals. The high values of the F and chi-squared statistics and their corresponding small p-values up to lag 2, there is an evidence to conclude that there is presence of ARCH effect in the return series even at 1% significant level.

Table 5:

Heteroskedasticity Test: ARCH

F-statistic	4.703207	Prob. F(2,726)	0.0093
Obs*R-squared	9.324470	Prob. Chi-Square(2)	0.0094

Result: It can be seen that $p<0.01$so, null hypothesis of No ARCH effect get rejected and indicating ARCH effect in residuals. To apply EGARCH model it is necessary to check the residuals obtained from mean equation for serial correlation and ARCH effect. There should be serial correlation in squared residuals and ARCH effect in residuals. So, by seeing the results of Table 6 we can ensure to proceed for EGARCH (1, 1) model.

EGARCH

Table 6:

Dependent Variable: LN_RETURNS
Method: ML ARCH - Normal distribution (BHHH / EViews legacy)
Date: 05/06/20 Time: 20:24
Sample: 1 731
Included observations: 731
Convergence not achieved after 500 iterations
Presample variance: backcast (parameter = 0.1)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000840	0.000333	2.521045	0.0117
Variance Equation				
C(2)	-0.889128	0.214555	-4.144054	0.0000
C(3)	0.212003	0.032561	6.510863	0.0000
C(4)	-0.117539	0.022378	-5.252546	0.0000
C(5)	0.922247	0.021323	43.25162	0.0000

R-squared	-0.000023	Mean dependent var	0.000791
Adjusted R-squared	-0.000023	S.D. dependent var	0.010158
S.E. of regression	0.010158	Akaike info criterion	-6.486457
Sum squared resid	0.075328	Schwarz criterion	-6.455032
Log likelihood	2375.800	Hannan-Quinn criter.	-6.474334
Durbin-Watson stat	1.896978		

- C2 = Constant, C3 = ARCH Effect, C4 = Leverage Effect, C5 = GARCH Effect.
- If C4 = 0, the model is symmetric.

But if C4 < 0, it implies that bad news(negative shocks) generate larger volatility than good news(positive shocks).

ARCH term is the square of past residual factors (e2) while GARCH is the past volatility (variance H) for general GARCH model and in the case of E-GARCH, it is the past values of log variance (H). C (5) is for the GARCH term. C (3) and C (4) is for the ARCH term, but the absolute value in C (3) is for the effect of the size, while C (4) is for the effects of sign (bad news vs. good news).

C3 is positive shows there is a positive relation between the past variance and the current variance in absolute value. C4 is negative indicates an asymmetric effect. Bad news will increase volatility more than a good new of the same size does - which is normally found in financial time series of stock prices and exchange rate.

In Table 6 it can be seen that ARCH and GARCH coefficients of variance equations are significant and positive in. Significant and positive value of ARCH Term (C3) indicates present volatility is significantly affected by previous period news information on volatility and presence of volatility clustering. Significant and positive value of GARCH Term (C5) indicates present volatility or conditional variance is significantly affected by previous period conditional variance.

C3 Values are close to one in Banking sectors indicating higher persistence of shocks of volatility. Leverage term coefficient in Bank sector is negative and significant so indicating presence of leverage effect means negative shocks have larger impact on volatility than positive shocks. Sum of C3 and C5 is greater than one indicating conditional variance is explosive means movement of indices will be destabilized due to volatility disturbances and possibility of permanent change in future behavior of these indices is there. Moreover, Impact of these disturbances could be reinforced over time. By seeing AIC and SIC information criteria it can be said that EGARCH Model best describes the Bank sector by giving lower values and Log likelihood giving higher values. EGARCH Model residual diagnostic–For EGARCH model diagnostic further ARCH effect is checked. From Table 7 it can be observed that Durbin Watson statistics is near to two indicating no autocorrelation after implementation of EGARCH model.

DIAGNOSTIC TEST FOR THE BEST FITTED EGARCH MODEL

Table7:

Heteroskedasticity Test: ARCH			
F-statistic	4.208318	Prob. F(1,728)	0.0406
Obs*R-squared	4.195626	Prob. Chi-Square(1)	0.0405

The null hypothesis that there is no remaining ARCH effect in the models is not rejected at 1% significant level based on the Chi-squared statistic. The conformity of the residuals of the estimated model to homoscedasticity is an indication of goodness of fit. The probability value of the Q-statistics in NEXT Table for all lags are higher than 0.01, confirming that there is no serial correlation in the standardized residuals of the estimated models at 1% significant level.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.065	0.065	3.1335	0.077
		2	-0.009	-0.013	3.1949	0.202
		3	-0.026	-0.025	3.6958	0.296
		4	0.002	0.005	3.6984	0.448
		5	-0.020	-0.022	4.0053	0.549
		6	0.017	0.019	4.2162	0.647
		7	0.009	0.006	4.2747	0.748
		8	-0.080	-0.082	8.9948	0.343
		9	0.023	0.036	9.3888	0.402
		10	0.017	0.012	9.6157	0.475
		11	0.038	0.035	10.700	0.464
		12	0.003	0.001	10.706	0.549
		13	-0.008	-0.011	10.814	0.626
		14	-0.060	-0.054	13.516	0.486
		15	-0.039	-0.031	14.661	0.476
		16	0.081	0.080	19.623	0.238
		17	0.010	-0.001	19.699	0.290
		18	0.027	0.027	20.239	0.320
		19	-0.002	0.001	20.243	0.380
		20	-0.018	-0.021	20.485	0.428
		21	-0.053	-0.047	22.611	0.365
		22	0.052	0.048	24.673	0.313
		23	0.003	-0.009	24.678	0.367
		24	-0.020	-0.005	24.970	0.407
		25	-0.052	-0.049	27.004	0.356
		26	-0.003	0.005	27.012	0.409
		27	0.059	0.055	29.681	0.329
		28	0.003	-0.015	29.688	0.378
		29	-0.031	-0.042	30.401	0.394
		30	-0.003	0.021	30.410	0.445
		31	0.063	0.071	33.493	0.347
		32	-0.021	-0.032	33.824	0.379
		33	0.002	-0.004	33.829	0.427
		34	-0.063	-0.070	36.905	0.336
		35	-0.071	-0.081	40.837	0.229
		36	-0.035	-0.020	41.760	0.235

FINDINGS AND CONCLUSION

This study is related to analyses the volatility of Bank Nifty of National Stock Exchange, India from January 2017 To December 2019 with the help of EGARCH model. It is analyzed that distribution of Bank sectors is deviated from normality and return series are stationary at level with constant and trend. EGARCH model is applied with student t distribution. Mean equation indicated that present period returns are significantly related with previous period returns by showing significant AR term. ARCH and GARCH coefficients of Banking sectors are positive and significant, indicating present volatility is significantly affected by previous period news information on volatility and present period conditional variance is significantly affected by previous period conditional variance respectively. GARCH Effect values are close to one in banking sectors indicating higher persistence of shocks of volatility, shocks take longer time to die out. Negative and significant leverage term coefficient in Banking sectors indicates presence of leverage effect means negative shocks have larger impact on volatility than positive shocks. Sum of constant (C2) and GARCH Effect (C5) is greater than one in Bank sectors indicating conditional variance is explosive in nature means movement of indices will be destabilized due to volatility disturbances and impact of these disturbances could be reinforced over time. Overall Banking sectors have heterogeneous responses towards volatility so requires attention not only from investment point of view but needs steps towards reforms also that can help in minimizing the volatility and stabiles its movement in future.

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