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MODELING CONDITIONAL VOLATILITY OF INDIAN BANKING SECTOR'S STOCK MARKET RETURNS

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Abstract

The study attempts 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 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; further evidenced from Markov regime switches. The exponential GARCH (EGARCH) model is found to be the best fit model capturing time-varying variance in the banking sector. The results support strong implications for the market participants at the time of devising portfolio management strategies.

Keywords: banking sector; conditional volatility; GARCH; sectoral indices; variances.

JEL classification: G00; G11.

1. INTRODUCTION

Ever since the recent global financial crisis, the countries are following divergent monetary policy initiatives in the wake of respective deflationary or inflationary pressures. The banking sector is one of the fundamental sectors that act as a medium to all other economic channels. It is one of the most interest rate sensitive sectors. The monetary policy initiatives undertaken by the Central Bankers have a direct impact on the volatility of the banking sector stock market returns. Furthermore, in an emerging market like India, both public as well as private sector banks are primarily supposed to undertake several priority sector lending initiatives. These initiatives further have an impact on the health of their financial statements over the years. So, all of these policy measures also have an impact on the volatility of the banking sector market returns. Consequently, the present study is an attempt to capture conditional variance of Indian banking sector stock market return volatility.

It is pertinent to mention that volatility is not directly observable rather depends on past observations. A simple measure to account for volatility is standard deviation or static variance. However, it is not a robust as well as a dynamic measure to capture time-varying

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aspect of volatility. So, the present study employs univariate GARCH based models to account for the same across the years 2005 to 2015. It is well documented that the GARCH based models are found to be more efficient in capturing stochastic time-varying variance as compared to other econometric models. The GARCH models bear the capability to capture various stylized features of financial markets relating to volatility clustering phenomenon, fat-tailed distributions, stochastic variance processes, etc. On simple terms, volatility can be defined as fluctuations in asset prices. The concept of volatility holds a prominent place in asset pricing, options pricing and various other risk management related aspects.

Numerous researchers have tried to account for time-varying variance in both developed as well as developing economies (for instance, French et al., 1987; Chou, 1988; Kenneth, 2013, etc.) using different econometric models. Kaur (2004) investigated stock market volatility patterns in the Indian equity market. The volatility in the Indian stock market exhibits patterns similar to those in many of the major developed and emerging stock markets, like volatility clustering and asymmetrical response to news arrival, meaning that the impact of good and bad news is not the same. Karmarkar (2007) found asymmetric volatility in the Indian equity market, whereby falling returns add to conditional variance as compared to positive financial shocks in the market. Using daily data from two Middle East stock market indices viz., the Egyptian CMA index and the Israeli TASE-100 index, Floros (2008) investigated conditional volatility by employing GARCH, EGARCH, TGARCH, Component GARCH (CGARCH), Asymmetric Component GARCH (ACGARCH) and Power GARCH (PGARCH) based models. The results indicated the existence of leverage effect and time varying variances. Esman Nyamongo and Misati (2010) investigated relationship between stock volatility and returns in the Nairobi Stock Exchange, Kenya using daily returns data over the period January 2006 to April 2009. The GARCH based regression models came out with the findings that volatility of returns is highly persistent with insignificant leverage effects and the impact of news on volatility is not significantly asymmetric.

Wei (2002) studied the performance of GARCH model and two of its non-linear modifications to forecast volatility in the Chinese stock market. The study came out with the finding that GARCH based models adequately capture conditional variance in the equity market. Goudarzi and Ramanarayanan (2010) examined volatility of Indian stock market using BSE 500 stock index and by employing ARCH and GARCH based models. The study found that GARCH (1,1) is the most appropriate model for capturing conditional volatility in the Indian equity market. Ahmed and Aal (2011) examined Egyptian stock market return volatility from 1998 to 2009 and further reported that EGARCH model is one of the best fit models among the other models for measuring time-varying volatility. On a similar note, Mittal et al. (2012) investigated volatility in the Indian equity market using daily returns from 2000 to 2010. The study reported that GARCH and PGARCH based models are found to be the best fit models to capture conditional variance in the Indian equity market.

Using ARCH based models, Lakshmi (2013) found out that the realty sector witness higher volatility than any other sectors in the Indian financial market. Similarly, Banumathy and Azhagaiah (2015) empirically investigated the volatility patterns of Indian stock market using daily closing prices of Nifty index for ten years period from 1st January 2003 to 31st December 2012. The authors support employment of GARCH (1,1) and TGARCH (1,1) estimations to capture symmetric and asymmetric volatility respectively. The asymmetric effects (leverage) show that negative shocks have significant effect on conditional variance (volatility). Tripathy and Gil-Alana (2015) investigated time-varying volatility in the Indian stock market by employing both symmetric as well as asymmetric GARCH models. The findings suggest that the volatility is persistent and asymmetric in the Indian equity market. The model under the generalized error distribution (GED) appears to be the most suitable one. Interestingly, the studies with respect to the Indian equity market sectors (like banking, pharmaceutical, information technology, infrastructure, realty, etc.) are much lesser. On this account, the present study is an attempt to account for conditional variances of banking sector stock market returns across the period 2005 to 2015 while considering the financial crisis period as well. The rest of the paper is organized as; Section 2 explains the empirical framework, Section 3 reports empirical findings and lastly Section 4 concludes the paper.

2. EMPIRICAL FRAMEWORK

To capture the conditional volatility of the banking sector stock market returns, the study uses S&P BSE Bankex index provided by Bombay Stock Exchange ltd. The index measures the performance of industries in the banking sector of the economy using modified market-cap-weighted methodology. The study further employs three different GARCH based models comprising ARMA (1,1) GARCH (1,1), ARMA (1,1) Threshold GARCH (1,1) and ARMA (1,1) Exponential GARCH (1,1) models to account for time-varying conditional variance. The span of daily data ranges from 1st January 2005 to 31st December 2015. The source of data is Bombay Stock Exchange (BSE). A well known concept in the area of financial economics is the existence of structural breaks in the financial dataset. In this regard, the time span which has been taken into consideration for the purpose of analysis also comprises the US subprime crisis events that got unearthed in the years 2007 to 2009. So, the time period ranging from 1st July 2007 to 30th June 2009 – as per the Business Cycle Dating Committee of the National Bureau of Economic Research (2010), the recovery from the US crisis started from June 2009 (Business Cycle Dating Committee) – is regarded as the existence of US financial crisis for the purpose of computation of conditional variance with 1 denoted as the existence of crisis and 0 otherwise. The stock market returns are computed in logarithmic terms:

$$R_t = Log\ (P_t / P_{t-1})*100 \quad (1)$$

where Rt is the daily return, Pt is the current day's price and Pt-1 is the previous day's price. As mentioned earlier, the study employs three different GARCH based models capturing symmetric as well as asymmetric conditional variance in the market:

A. ARMA (1,1) GARCH (1,1) model

The plain vanilla ARMA (1,1) GARCH (1,1) model ascertains time-varying variance, however, it cannot ascertain the specific impact of a negative shock on the volatility, due to the assumption of the symmetric impact of a positive and a negative shock (Bollerslev, 1986). The term Autoregressive Moving Average (ARMA) is the 'mean' equation of the model. The residuals derived from the mean equation are further modeled to account for conditional variance.

Mean equation:

$$R_t = c + pR_{t-1} + \gamma e_{t-1} + \varepsilon_t \quad (2)$$

where R_t is stock market return, c is constant term, p captures impact of one day lagged return on current conditional return, γ captures impact of one day lagged market news on current conditional return and ε_t is the residual term; expected to be white noise.

Variance equation:

$$h_t = \alpha_0 + a_1 u_{t-1}^2 + \beta_1 h_{t-1} + \gamma dummy \qquad (3)$$

where h_t is the conditional variance, u_{t-1}^2 is lagged error term, h_{t-1} is lagged conditional variance. The lagged values of conditional variance in the variance equation show persistency level of the volatility and the error terms captures news impact on the volatility. The dummy variable captures the impact of US financial crisis on conditional variance. The GARCH (1,1) model shall be stationary when $\alpha_1 + \beta_1$ is less than unity.

B. ARMA (1,1) TGARCH (1,1) model

The TGARCH model, also known as GJR model (Glosten et al., 1993), analyses the impact of a negative shock on the conditional volatility or in short the 'leverage effect'. The 'mean' equation is similar to the earlier version of GARCH model.

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \delta \varepsilon_{t-1}^2 D_{t-1} + \beta_1 h_{t-1} + \gamma dummy \qquad (4)$$

where, D_{t-1} is a dummy variable to ascertain the leverage impact of a negative shock. If $\varepsilon_{t-1} < 0$, then the value 1 is assigned and otherwise zero. If δ is found to be significant and positive, then a negative shock has a leverage impact on the conditional variance $(\alpha_1 + \delta)$ as compared to the positive one. On a similar note, α_1 and β_1 captures the news impact and the persistency impact on conditional volatility respectively.

C. ARMA (1,1) EGARCH (1,1) model

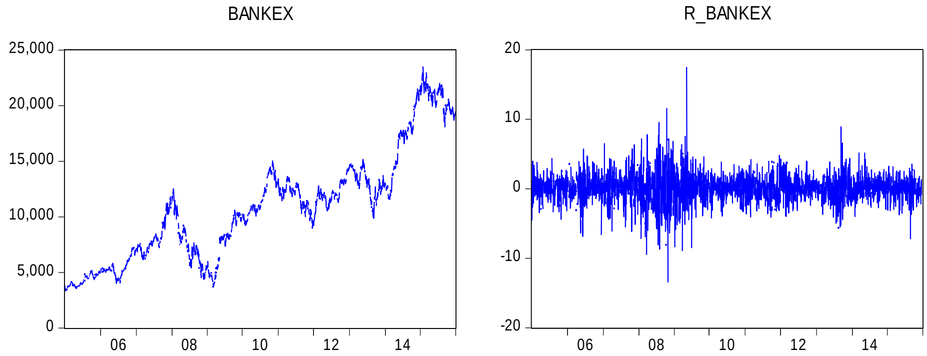
Another important model is EGARCH model which also accounts for 'leverage effect'. The model has been developed by Nelson (1991). The term 'leverage effect' relates to a situation when falling returns have an increasing impact on the conditional variance owing to increase in debt to equity ratio (Black, 1976; Christie, 1982). The 'mean' equation is similar to the earlier version of GARCH model.

$$log h_t = \alpha_0 + \alpha_1 \left(\frac{|\varepsilon_{t-1}|}{h_{t-1}} - \sqrt{\frac{2}{\pi}} \right) + \delta \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_1 h_{t-1} + \gamma dummy \qquad (5)$$

where δ is the asymmetry coefficient capturing asymmetric response of conditional variance toward negative and positive shocks. The leverage effect will be there when $\delta < 0$ and found to be significant. Similarly, α_1 and β_1 captures the news impact and the persistency impact on conditional volatility respectively. Again the dummy variable captures the impact of financial crisis on conditional variance. All the GARCH models are modelled assuming student-t distribution of the index error terms supported by Quantile-Quantile plots.

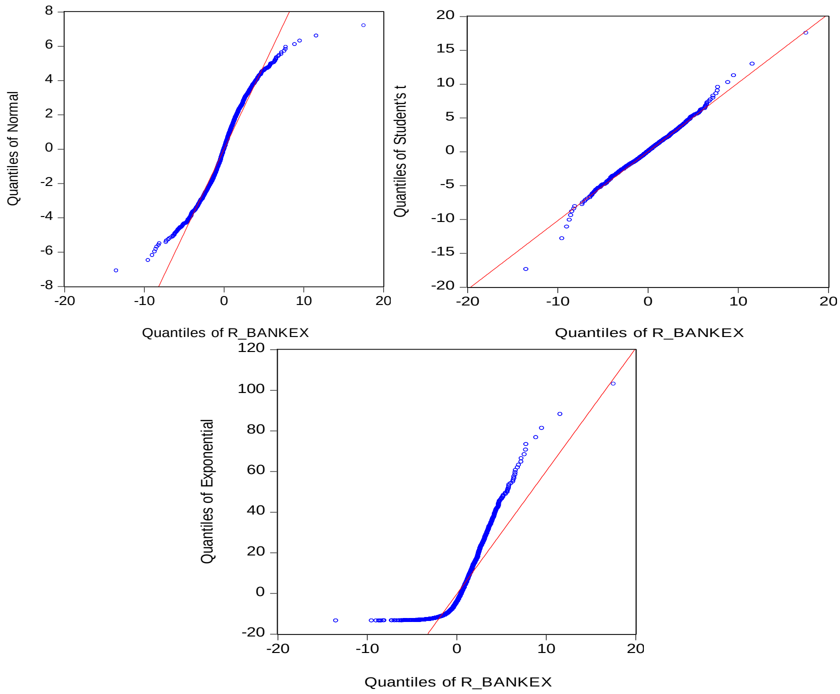
3. EMPIRICAL FINDINGS AND DISCUSSION

Figure no. 1 is the graphical presentation of Indian banking index returns and price levels over the years 2005 to 2015. The index has registered around 16 percent compounded annual growth rate across 11 years. More interestingly, it has even surpassed its previous highest level witnessed before the US financial crisis. As expected, the index returns are highly volatile wherein period of high volatility is followed by the higher ones and period of low volatility is followed by the lower ones. This is termed as 'volatility clustering' phenomenon thereby justifying application of the GARCH based models in the presence of heteroskedastic distributions. Notably, the QQ plots (Figure no. 2) support employment of student-t distribution for modeling conditional variances because quantiles of the index returns are substantially on straight line.



Source: author's computations

Figure no. 1 – S&P BSE Bankex index



Source: author's computations

Figure no. 2 – Quantile-Quantile Plots

On an average, daily index returns are 0.06 percent, whereas the standard deviation of the same is around 2. The skewness value is positive indicating greater probability of positive returns. On the other hand, the kurtosis value is greater than three thereby indicating leptokurtic distributions of index returns. Furthermore, augmented Dickey-Fuller (ADF) test confirms stationary distribution of index returns [-45.7879; p<0.0000]. One of the main pre-conditions for the application of GARCH based models is the existence of ARCH effects in the residuals derived from the 'mean' equation. The ARCH effects test confirms the existence of heteroskedastic error terms derived from the 'mean' equation [34.3784; p<0.0000] taking 10 days lagged values. Moreover, the residuals are found to be substantially white noise. Table no. 1 reports ARMA (1,1) GARCH (1,1) model results. One day lagged return in the banking sector does not have a statistically significant impact on the current conditional return. Moreover, one day lagged news component or market shocks also do not have a statistically significant impact on the conditional returns.

Table no. 1 – ARMA (1,1) GARCH (1,1) model results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.103241	0.032558	3.170988	0.0015
AR(1)	-0.081153	0.144559	-0.561388	0.5745
MA(1)	0.213193	0.141258	1.509244	0.1312
Variance Equation				
C	0.078161	0.021982	3.555663	0.0004
$\boldsymbol{\alpha_1}$	0.070270	0.012150	5.783648	0.0000
$\boldsymbol{\beta_1}$	0.898640	0.016402	54.78899	0.0000
$\boldsymbol{\gamma}$	0.267738	0.091989	2.910553	0.0036
T-DIST. DOF	7.643734	1.097212	6.966508	0.0000

Source: author's computations

Table no. 2 – Standardized Residuals: GARCH (1,1)

Lags	AC	PAC	Q-Stat	Prob*
1	0.013	0.013	0.4515	
2	-0.002	-0.003	0.4678	
3	-0.010	-0.010	0.7604	0.383
4	-0.005	-0.004	0.8205	0.663
5	-0.024	-0.023	2.3370	0.505
6	-0.030	-0.029	4.7234	0.317
7	0.012	0.013	5.1424	0.399
8	0.002	0.001	5.1542	0.524
9	0.027	0.027	7.2191	0.406
10	0.001	-0.000	7.2205	0.513
11	0.002	0.001	7.2358	0.613
12	0.006	0.006	7.3322	0.694

Source: author's computations; AC is Autocorrelation and PACF is Partial Autocorrelation

Under the variance equation, one day lagged market shock has a significant impact on the current conditional variance. However, the impact of past volatility is greater in magnitude as compared to recent market shocks. The coefficient for the dummy variable is also found to be significant at 5 percent significance level indicating an increased level of volatility in the banking sector return during the financial crisis period. The sum of ARCH and GARCH effects is less than one indicating stationary distribution of the model results. Moreover, Tables no. 2 and no. 3 support usage of one day lagged market events only as all the Ljung Box test statistics are insignificant for all the residual lags. Table no. 4 reports ARMA (1,1) TGARCH (1,1) model results. All the results are similar to the basic GARCH model mentioned above except for the impact of recent market shocks on conditional variance. But TGARCH model also reports the existence of leverage effect in the banking sector returns. In other words, there is a negative relationship between current returns and future volatility in the market.

Table no. 3 – Squared Residuals GARCH (1,1)

Lags	AC	PAC	Q-Stat	Prob*
1	-0.006	-0.006	0.0981	0.754
2	0.008	0.008	0.2631	0.877
3	-0.012	-0.012	0.6633	0.882
4	-0.023	-0.023	2.1196	0.714
5	-0.026	-0.026	3.9196	0.561
6	0.024	0.024	5.5007	0.481
7	0.006	0.007	5.6119	0.586
8	-0.025	-0.027	7.3388	0.501
9	0.025	0.024	9.1089	0.427
10	-0.009	-0.008	9.3245	0.502
11	-0.006	-0.006	9.4403	0.581
12	0.010	0.009	9.7017	0.642

Source: author's computations; AC is Autocorrelation and PACF is Partial Autocorrelation

Table no. 4 – ARMA (1,1) TGARCH (1,1) model results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.073812	0.032405	2.277808	0.0227
AR(1)	-0.078550	0.139179	-0.564380	0.5725
MA(1)	0.214287	0.136155	1.573849	0.1155
Variance Equation				
C	0.101480	0.023114	4.390371	0.0000
$\boldsymbol{a_1}$	0.013723	0.011098	1.236488	0.2163
$\boldsymbol{\delta}$	0.110446	0.021371	5.167940	0.0000
$\boldsymbol{\beta_1}$	0.891386	0.016815	53.01232	0.0000
$\boldsymbol{\gamma}$	0.302546	0.095980	3.152184	0.0016
T-DIST. DOF	7.745728	1.082593	7.154790	0.0000

Source: author's computations

The coefficient is found to be positive and significant. Once again, coefficient for the dummy variable is found to be significant at 5 percent significance level. Moreover, Tables no. 5 and no. 6 support usage of one day lagged market events only as all the Ljung Box test statistics are insignificant for all the residual lags.

Table no. 5 – Standardized Residuals: TGARCH (1,1)

Lags	AC	PAC	Q-Stat	Prob*
1	0.014	0.014	0.5302	
2	-0.002	-0.002	0.5408	
3	-0.009	-0.009	0.7812	0.377

Lags	AC	PAC	Q-Stat	Prob*
4	0.003	0.004	0.8135	0.666
5	-0.023	-0.023	2.3058	0.511
6	-0.031	-0.031	4.9594	0.291
7	0.007	0.008	5.1056	0.403
8	-0.001	-0.001	5.1066	0.530
9	0.029	0.029	7.4747	0.381
10	0.004	0.003	7.5098	0.483
11	0.007	0.006	7.6556	0.569
12	0.003	0.003	7.6868	0.659

Source: author's computations; AC is Autocorrelation and PACF is Partial Autocorrelation

Table no. 6 – Squared Residuals: TGARCH (1,1)

Lags	AC	PAC	Q-Stat	Prob*
1	-0.005	-0.005	0.0642	0.800
2	-0.004	-0.004	0.1023	0.950
3	-0.012	-0.012	0.4974	0.919
4	-0.015	-0.015	1.0729	0.899
5	-0.021	-0.021	2.2885	0.808
6	0.016	0.016	3.0134	0.807
7	0.005	0.005	3.0892	0.877
8	-0.027	-0.027	5.0743	0.750
9	0.017	0.017	5.9063	0.749
10	-0.002	-0.002	5.9149	0.822
11	0.004	0.005	5.9673	0.876
12	0.010	0.010	6.2423	0.903

Source: author's computations; AC is Autocorrelation and PACF is Partial Autocorrelation

Table no. 7 reports ARMA (1,1) EGARCH (1,1) model results. All the findings are similar to the other models reported earlier and even one day lagged market shock is found to be having a statistically significant impact on current conditional variance at 5 percent significance level. The asymmetric coefficient is found to be negative and significant highlighting asymmetric response of conditional variance toward negative shocks. Moreover, it also indicates increased level of conditional variance during the financial crisis period.

Table no. 7 – ARMA (1,1) EGARCH (1,1) model results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.069568	0.032139	2.164625	0.0304
AR(1)	-0.087693	0.138384	-0.633696	0.5263
MA(1)	0.222065	0.135474	1.639172	0.1012
Variance Equation				
C	-0.064951	0.016225	-4.003153	0.0001
$\boldsymbol{a_1}$	0.129635	0.022690	5.713409	0.0000
$\boldsymbol{\delta}$	-0.087159	0.014817	-5.882418	0.0000
$\boldsymbol{\beta_1}$	0.957407	0.008854	108.1382	0.0000
$\boldsymbol{\gamma}$	0.062732	0.015136	4.144553	0.0000
T-DIST. DOF	7.873049	1.118626	7.038140	0.0000

Source: author's computations

Table no. 8 – Standardized Residuals: EGARCH (1,1)

Lags	AC	PAC	Q-Stat	Prob*
1	0.016	0.016	0.6591	
2	-0.005	-0.005	0.7342	
3	-0.008	-0.008	0.9082	0.341
4	0.003	0.003	0.9317	0.628
5	-0.021	-0.021	2.1133	0.549
6	-0.028	-0.027	4.2692	0.371
7	0.006	0.007	4.3679	0.498
8	-0.002	-0.003	4.3769	0.626
9	0.029	0.029	6.7050	0.460
10	0.003	0.002	6.7362	0.565
11	0.006	0.005	6.8391	0.654
12	0.002	0.002	6.8492	0.740

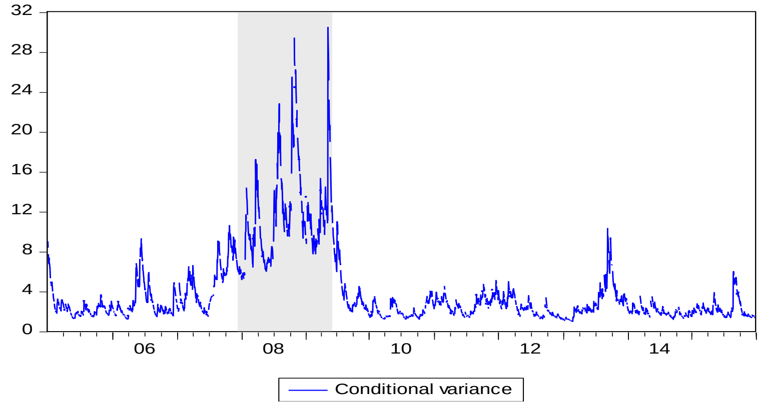
Source: author's computations; AC is Autocorrelation and PACF is Partial Autocorrelation

Table no. 9 – Squared Residuals: EGARCH (1,1)

Lags	AC	PAC	Q-Stat	Prob*
1	0.003	0.003	0.0227	0.880
2	0.005	0.005	0.1010	0.951
3	-0.010	-0.010	0.3934	0.942
4	-0.012	-0.012	0.7616	0.944
5	-0.014	-0.014	1.3130	0.934
6	0.019	0.019	2.2759	0.893
7	0.010	0.009	2.5241	0.925
8	-0.028	-0.029	4.6634	0.793
9	0.025	0.025	6.3214	0.707
10	0.001	0.001	6.3223	0.788
11	0.009	0.009	6.5637	0.833
12	0.013	0.013	7.0264	0.856

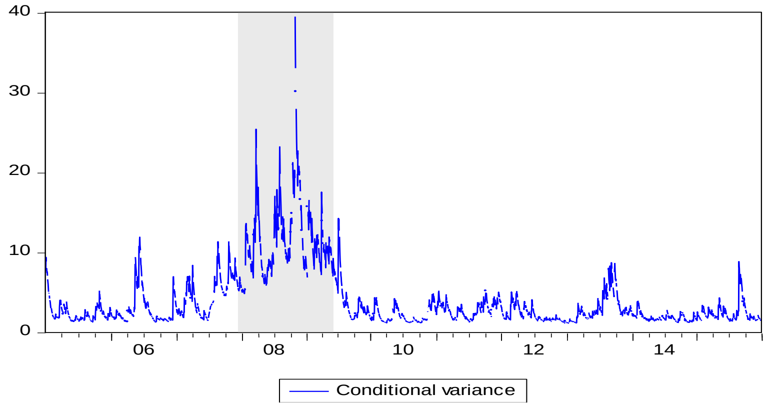
Source: author's computations; AC is Autocorrelation and PACF is Partial Autocorrelation

Tables no. 8 and no. 9 support usage of one day lagged market events only as all the Ljung Box test statistics are insignificant for all the residual lags. All the univariate GARCH models are found to be adequate in the context that the standardized residuals derived from the variance equations are found to be white noise and homoskedastic; evidenced from ARCH-LM test [for GARCH model (0.0978, p>0.10); EGARCH model (0.0226, p>0.10); TGARCH model (0.0640; p>0.10)]. The study also reports graphical distribution of conditional variances generated from all the GARCH based models (see Figures no. 3, no. 4 and no. 5). All the models spotlight excessive volatile nature of the banking sector market returns across the years 2005 to 2015. The volatility was at its highest level during the years 2007 to 2009, when the subprime crisis got unleashed in the US and more prominently during the Lehman Brothers' episode. After the crisis period, conditional variance has returned to its normal level.



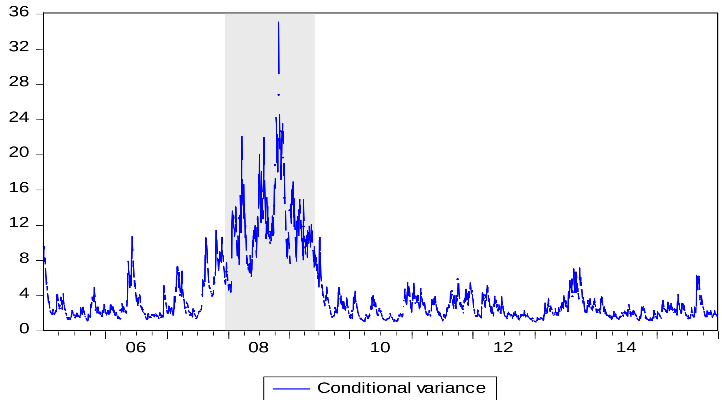
Source: author's computations

Figure no. 3 – Conditional Variance: GARCH (1,1) model



Source: author's computations

Figure no. 4 – Conditional Variance: TGARCH (1,1) model



Source: author's computations

Figure no. 5 – Conditional Variance: EGARCH (1,1) model

The results reported by GARCH based models highlight a significant understanding with respect to the banking sector market return volatility. The conditional volatility is significantly affected by its own past values instead of recent market shocks in magnitude terms. Moreover, its response is not symmetric in nature whereby negative shocks further increases volatility in the banking sector returns.

Table no. 10 – Markov Switching results: EGARCH (1,1) model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
C	12.22896	0.113106	108.1191	0.0000
Regime 2				
C	2.624353	0.042628	61.56470	0.0000

Source: author's computations

Overall, the Akaike's information criteria (AIC) and log likelihood values support EGARCH model as one of the best fit model [for GARCH model (AIC: 3.91 and LL: -5332.550); EGARCH model (AIC: 3.89 and LL: -5309.613); TGARCH model (AIC: 3.90 and LL: -5314.134). Accordingly, we further attempt to gather response of the conditional variances (generated from EGARCH model) toward dynamic shocks during the sample years. In other words, we attempt to understand dynamic movement (regimes) of the volatile patterns across the sample years undertaken. For this purpose, Markov regime switching model is also employed, wherein the conditional variances are subjected to different regimes (two regimes for the sake of parsimonious model). The null hypothesis with no switching works as follows (Hamilton, 1989 and Schaller and Norden, 1997):

$$C_t = a_0 + \sigma_0 \varepsilon_t \quad (6)$$

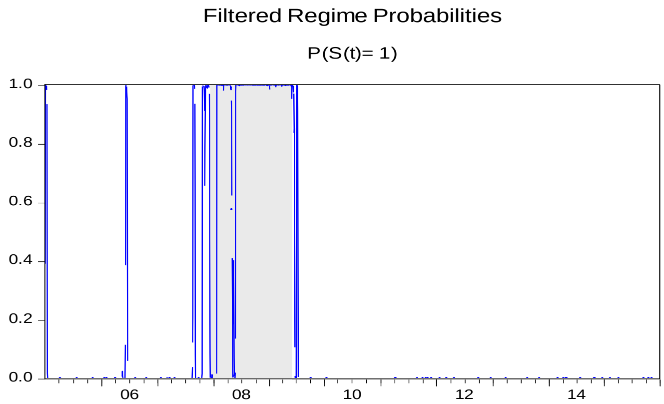
where, C_t is the conditional variance at time t, a_0 and σ_0 are the unconditional mean and standard deviation and ε_t is the error terms expected to be white noise. The alternate hypothesis states switching at the 'mean' level only.

$$C_t = a_0(1 - S_t) + a_1 S_t + \sigma_0 \varepsilon_t \quad (7)$$

where, S_t is the state dependent 'mean' and an unobserved discrete variable that represents a state or regime. The model follows a first order Markov chain. In other words, the probability that a given state will occur during this period depends on the state last period, i.e. the probability that state 1 (2) will persist from one period to the next is p (q). The study uses Garcia's (1992) distribution of the likelihood ratio for hypotheses testing due to the non-existence of any standardized test and the presence of non-standard asymptotic distributions.

Table no. 10 reports Markov regime switching results, whereby regime-1 is denoted as 'high volatility' regime and regime-2 is denoted as 'low volatility' regime. The regimes are categorized purely on the basis of their relative comparisons.

Lastly, Figure no. 6 reports filtered probabilities for the existence of first regime, i.e. higher volatility regime across the sample years. On an expected note, probability for the existence of higher volatile patterns in the banking sector index returns augmented near to one during the US financial crisis episodes. It shows that the EGARCH model has really captured major economic shocks in the global markets while modeling conditional variances in the Indian banking sector returns on account of liberalized financial flows. The findings are consistent with the ones supporting employment of GARCH based models, volatility persistency and leverage effects in the market.



Source: author's computations

Figure no. 6 – Markov Switches: EGARCH (1,1) model

Recently, Mallikarjuna and Prabhakara (2017) also reported volatility persistence and leverage effects in the Indian banking sector returns but with a sample period ranging only from 2010 to 2015. On a similar note, Birau et al. (2015) supported volatility clustering phenomenon in the Indian banking sector returns, however, with no direct modeling of asymmetric volatile patterns in the latter market. Interestingly, Singh and Makkar (2014) also reported significant impact of crisis events on the Indian banking sector index but by considering only symmetric aspect of the conditional variances. Contrary to this, the present study attempted to model conditional variances in the Indian banking sector returns by employing both symmetric as well as asymmetric variance models coupled with regime switches.

4. CONCLUDING REMARKS

The present study attempted to model time-varying variance of banking sector returns in India across the years 2005 to 2015 by employing different univariate GARCH based models. The results report existence of persistency as well as leverage effects in the Indian banking sector. The past volatility has a greater magnitude impact on current conditional variance. Similarly, the response of conditional variance is asymmetric towards negative market shocks. For instance, negative returns increase conditional volatility in the market. The Akaike Information Criteria (AIC) and log likelihood values support EGARCH model as one of the best fit model (consistent with Ahmed and Aal, 2011). The results support strong implications for the portfolio managers as well as different market participants. Volatility in the market has an impact on overall correlation coefficients and risk-return dynamics prevalent in the respective markets. It is one of the important parameters determining prices in derivative as well as cash markets. So, time-varying volatility holds an important place in the financial economics; placing greater emphasis on banking sector return volatility because all other economic channels are driven by the financial existence of banks in an economy.

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