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Modelling the volatility of banking sectors of national stock exchange

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Abstract

Objective: To model the conditional volatility of banking sectors of National Stock Exchange, India and to capture its dynamics as volatility clustering, persistence and leverage effect.
Methodology: Volatility is analysed by applying EGARCH model on daily returns data of two sectors namely composite Bank sector (Bank) and PSU Bank sector (PSU).
Findings: 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. Volatility shocks take time to die out in both sectors. Volatility of both sectors is explosive in nature.
Applications: Finding is helpful in taking decisions regarding investment and reforms in banking to stabilize the volatility.
***Keywords*:** PSU Bank, Bank and EGARCH model.

1. Introduction

Stock market volatility has received considerable attention in emerging markets. The importance of volatility is widespread in the area of financial economics because volatility plays an important role in asset price modeling. Volatility refers to the degree to which asset prices tend to fluctuate. It deals with variability or randomness of asset prices. It shows the range to which the price of a security may increase or decrease. It may be associated with risk that ultimately affects prices of assets. It is affected by information on inflation, government policies and decisions, business and industries conditions and other fundamental factors of economy. Volatility has impact on investment and risk management decisions so portfolio managers, risk arbitrageurs, and corporate treasurers closely watch assets price's volatility and its trends to form their strategies to invest. India is an emerging market and study of volatility of its stock market indices is of keen interest for all investors investing in it. Volatility is time varying that change with time and characterized with swings. It is measured as standard deviation or variance of returns in financial return series.

Volatility is said to be conditional when its current period estimates depend on previous period estimates. To model this conditional volatility or conditional variance ARCH (Autoregressive conditional heteroskedasticity) and EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) models are used.

Indian banking sector is sufficiently capitalized and well-regulated. Superior financial and economic conditions of the country are contributing to healthy growth of banking sector. Studies on credit, market and liquidity risks suggest that Indian banks are generally resilient and have withstood the global downturn well. The Indian banking system consists of 27 public sector banks, 26 private sector banks, 46 foreign banks, 56 regional rural banks, 1,574 urban cooperative banks and 93,913 rural cooperative banks, in addition to cooperative credit institutions. Public-sector banks control more than 70% of the banking system assets, thereby leaving a comparatively smaller share for its private peers. (Source- websitehttps://www.ibef.org/industry/banking-india.aspx).

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Measures of the government and regulator RBI for the recovery of non-performing assets (NPAs), increased levels of provision on the loans, rising of funds through issuance of rupee-denominated bonds overseas, called masala bonds, National Bank for Agriculture and Rural Development (NABARD) support to provide point-of-sale (PoS) machines in villages and RuPay cards to farmers across India, India's indigenous digital payments application- BHIM (Bharat Interface for Money), mobile and internet banking services, payments and small finance banksetc are strengthening banking sector of India and its business growth.

Banking sector is an important sector for investors to invest so the analysis of volatility in banking sector stocks becomes important. This analysis is done with the help of volatility modelling to measure conditional variance and capture volatility dynamics like clustering, persistence and leverage effect. So the current study is related to examine and model the volatility of PSU bank and Bank sector indices of NSE (National stock exchange), India. PSU Bank sector index includes stocks of only Public sector banks while Bank sector includes stocks from Public and private sector both. This study makes investors, regulator and policy makers to be rational for banking sectors shocks

2. Literature survey

Various studies on modelling the volatilities are there in literature analysing volatility dynamics, few of them are as follows: In [2] modelled the volatility for daily and weekly returns of Portuguese stock index PSI-20 and confirmed that there were significant asymmetric shocks to volatility in daily stock returns but not in weekly stock returns. Persistence in conditional volatility was different in sub periods. In [3] estimated conditional volatility models for S&P nifty and BSE Sensex to know the patterns of volatility like time varying, persistence, predictability and leverage effect of both indices and 50 individual stocks of Nifty using and found that eight stocks showed significant leverage effect. In [5] investigated the asymmetric relation between stock price and its volatility in India by taking BSE500 stock index and concluded that return series found to react asymmetrically to good and bad news. Bad news had high impact on volatility than good one. In [6] examined the Karachi Stock Exchange before and during financial crisis of 2008 and confirmed that EGARCH model was best at forecasting for both periods and GJR and EGRACH both captured the asymmetric effect of volatility significantly. In [7] examined sector specific volatility to determine sectoral response to shocks of the market in two periods, pre revolution (2007-10) and during revolution (2011-12). By taking 12 sectoral indices daily returns it was confirmed that TGARCH model was best fitted model in capturing the volatility characteristics. There was strong evidence of heterogeneous responses of different sectors for shocks on volatility. In [8] investigated the six sectoral indices of NSE to analyse volatility, forecast indices value, correlation and to suggest trading strategies. Coefficient of variance, descriptive statistics, correlation and least square method was used to analyse data and confirmed that CNX FMCG was consistent having low volatility and CNX IT was aggressive index during study period. Few sectors showed perfect positive correlation between them while few sectors showed poor negative correlation. Active strategy suitable for speculators while active strategy for investors. In [9] investigated the stock price behaviour and modelling the volatility of Indian stock market by exploring the features like heteroskedasticity, volatility clustering and fat tails of return series. Using the daily closing prices of S&P CNX Nifty it was confirmed that GARCH (1, 1) was best to capture symmetric effect of heteroskedasticity and PARCH (1, 1) model was best to capture asymmetric effect of leverage as per AIC and LL criteria it also showed volatility persistence. ARCH in mean reported that Indian market does not offer risk premium to take high risk because it is inefficient. In [10] modelled the volatility of Khartoum stock exchange, KSE from Sudan and Cairo and Alexandria stock exchange index CMA, from Egypt with symmetric and asymmetric GARCH models and concluded that conditional variance for KSE was an explosive process while for CASE it was quite persistent, evidence were found for positive risk premium and existence for leverage effects in two markets. In [11] investigated the volatility of 3 Asian markets Kuala lampur composite Index of Malaysia, Jakarta stock exchange composite Index of Indonesia and straits times Index of Singapore. GARCH (1, 1) and GARCH-M (1, 1) symmetric models were found to be sufficiently capturing persistent volatility clustering effect. In Indonesia Grach in mean effect (risk & return) was found with positive and significant correlation but in other two markets this effect was not found means increased risk did not necessarily cause increase in returns. In [12] examined the volatility of Nigerian banking sector indices and all share indexes. GARCH (1, 1) and GJR GARCH (1, 1) results evidenced for volatility clustering and persistence further innovations were insignificantly influencing stock return.

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In [13] investigated the long term volatility of R.P.G.U(Romania, Poland, Greece and USA) by using GARCH(1,1) model and confirmed that in first two emerging markets Poland was better as an investment option while in next two developed markets USA was better as an investment option. In [14] examined the risk and return parameters of nine sectoral indices of BSE to suggest for portfolio construction. Log mean, standard deviation, skewness, kurtosis and value at risk (VaR), performance measures like Sharpe, Treynor and Jensen) and Correlation were used for this purpose. It was confirmed that FMCG, CD and Auto were in top position in performance while Metal, IT and O&G was at lowest. In [15] analysed the volatility of NSE nifty and its sectoral indices. On the basis of Descriptive analysis and autocorrelation and exponential trend it was found that correlation was significant for most of the sectoral Indices except Metal, Pharma, PSU Bank and reality index. It was also confirmed that Pharma, PSU Bank indices have more impact on Nifty during study period. Study was suggestive to reduce risk and increase returns of investments. In [16] analysed the asymmetric leverage effect of political risk on return volatility of Borsa Istanbul sub sector index by determining breaks in unconditional variance and TGARCH model. It was confirmed that political risk that caused breaks in variance caused asymmetry and leverage effect on return volatility of XGAGT, XTAST, XMANA and XMASY sub sectors index returns. In [17] examined the Saudi stock market TASI to estimate and forecast its volatility. It was confirmed that asymmetric GARCH models were better than symmetric GARCH in estimating conditional variance and GJR model outperformed than other two models. In [18] confirmed that macro-economic factors like returns of debt and equity have significant impact on banking companies in India.

3. Data methodology and objective

1. Objective

This study is to model the volatility of PSU bank and composite Bank sector index to examine the volatility dynamics as volatility clustering, leverage effect and volatility persistence and their impact.

2. Data and its source

In present study two sectoral indices as CNX PSU bank and CNX Bank have been taken. Data in form of daily closing prices of these indices has been taken from NSE website from 1st April 2011 to 31 March 2017. Logged returns have been obtained from daily closing prices to use in models.

Return Series = Log (Pt/Pt-1)*100.

3. Descriptive statistics

This is used to find the distribution of returns.

4. ADF test

Augmented dickey fuller test is used to find the stationarity of return series.
ADF test of unit root with constant and trend have the following equation:

$$\Delta Y_t = \propto + \beta t + \gamma Y_{t-1} + \sum_{j=1}^{p} \left(\delta_j \Delta Y_{t-j}\right) + e_t \qquad (1)$$

Where:

Δ = first difference operator, Y_t= Time series value at time t and Y_{t-1}= Time series value lagged by one periodt is the time index, α is an intercept/constant. β is the coefficient on a time trend, γ is the coefficient presenting process root. p is the lag order of the first-differences autoregressive process and e_t is residual term. **H0** = y series contains unit root or non-stationary against **H1**= y series is stationary.

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If absolute value of test statistics is greater than critical value then Null hypothesis get rejected it means series is stationary. 1st difference of series is taken in case of non-stationary series to make it stationary. ARCH and EGARCH models are used to find conditional variance by assuming conditional heteroskedasticity. Heteroskedasticity found in financial time series returns is characterised by serial correlation, volatility clustering and persistence etc.

5. AR model

AR (1) autoregressive model time-varying processes in which output variable depends linearly on its own lagged values and on a random term. It is the representation of stochastic process. It works under the notion that past values have an effect on current values. AR (1) is the first order process, meaning that the current value is based on the immediately preceding value. In AR (2) process the current value is based on the previous two values.

To model the mean equation of index returns AR (1) process is specified as:

$$Xt = \alpha_0 + \alpha_1 X_{t-1} + \varepsilon_t \quad (2)$$

Where α_0 is constant, α_1 is coefficient to be measured of lagged return and ε_t is error term having zero mean and constant variance. Through linear regression residuals are obtained from the above AR (1) model to check serial correlation between them and then ARCH effect is tested on squared residuals.

6. ARCH model

Autoregressive Conditional Heteroskedasticity model introduced by [19] to model time varying volatility or forecast conditional variance.ARCH models assume the variance of the current error term or innovation to be a function of the previous time periods' error terms. This model captures the volatility clustering observed in series returns.

ARCH model specifications:

$$y_t = \mu_t + \varepsilon_t \quad , \qquad where \varepsilon_t = z_t \sigma_t$$

$\mu_t = E_{t-1}(y_t)$ is conditional mean information set at time t-1 or non-stochastic component that is predictable andε_t is error term or shock or stochastic component that is unpredictable, z_t is iid (independent and identical distributed random variables with zero mean and unit variance means iid (0, 1).
$y_t$andε_t has a conditional varianceσ_t^2 given by as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 \qquad (3)$$

ARCH effect means heteroskedasticity is modelled as conditional variance of squared residuals obtained from mean equation as from AR (1) model. ARCH (q) specification for conditional variance σ_t^2 is as follows-

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots\cdots\cdots + \alpha_q \varepsilon_{t-q}^2 \qquad (4)$$

H0 = $\alpha_0 = \alpha_1 = \alpha_2 \cdots\cdots\cdots = \alpha_q = 0$ (No ARCH Effect)
Against **H1**= $\alpha_0 \neq \alpha_1 \neq \alpha_2 \cdots\cdots\cdots \alpha_q \neq 0$ (ARCH Effect)

If value of test statistic is greater than critical value from chi square distribution or coefficient of α is statistically significant or p value less than 0.05 then null hypothesis is rejected.

7. Serial correlation

The checked before applying EGARCH model. Serial correlation in squared residuals is indication of ARCH effect. Ljung-Box Q* statistic to check serial correlation is as follows:

$$LB = N(N+2) \sum_{k-1}^{m} \left(\frac{\hat{\rho}_k^2}{N-K}\right) \qquad (5)$$

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Where N is the sample size, m is the number of lags being tested and $\hat{\rho}_k$ is the sample autocorrelation at lag k.

H0 = There is no autocorrelation in series.

8. EGARCH (1, 1) model

The developed by [20] is popular to capture the asymmetric volatility. GARCH model is symmetric model where conditional variance is dependent on only magnitude of shocks of returns while it does not consider positivity and negativity of shocks. Volatility shocks as per GARCH model may or may not be persistent. EGARCH (1, 1) model is a better estimate the volatility for asset than classic GARCH model because it covers the limitations of classic GARCH. EGARCH is an asymmetric model where it responds differently according to positive and negative shocks to returns. This asymmetric response to positive and negative shocks is called leverage effect. In other words, tendency of volatility to rise when returns fall and to decline when returns rise is leverage effect. EGARCH model captures such asymmetric or leverage effect.

The model has two equations mean and variance equations.

$$\text{Mean Equation - } Rt = \alpha_0 + \alpha_1 R_{t-1} + \varepsilon_t$$

Where R_t is the return at time t, α_0 is the constant or average return and ε_t is error term or residual returns. β_0 and β_1 are coefficients of error term and its lags.

$$\text{Variance Equation - } log\sigma_t^2 = \alpha_0 + \alpha_1|\varepsilon_{t-1}/\sigma_{t-1}| + \beta_1 log\sigma_{t-1}^2 + \gamma_1(\varepsilon_{t-1}/\sigma_{t-1}) \quad (6)$$

Where, α_0 is the constant α_1 is the arch term coefficient and β_1 is the coefficient of Garch term. γ is asymmetric response or leverage parameter. Log of conditional variances ensures forecasts of variance to be non-negative.

If $\gamma \neq 0$ it means there is asymmetric impact. If $\gamma < 0$ and significant it indicates presence of leverage effect means negative shocks have larger impact on next period conditional variance as compared to positive shocks while if $\gamma > 0$ and significant it indicates positive shocks have larger impact on next period conditional variance as compared to negative shocks.

4. Results and Discussions

1. Descriptive statistics

Table 1 it can be seen that bank sector returns are positive while PSU sector banks are showing loss during the study period. The Bank sector positive returns may be due to Private sectors stocks contribution. Standard deviation is also high in PSU sector indicating more risk and volatility. Both sectors are 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 are much higher and its p-values are less than 0.05 indicating returns are deviated from normal distribution.

Table 1. Descriptive statics

Description	Daily	
	Bank	PSU Bank
Mean	0.0177	-0.0068
Median	0.0183	0.0097
Std. Dev.	0.6474	0.8713
Skewness	0.1027	0.1442
Kurtosis	5.1470	4.8416
Jarque-Bera	288.2082	215.2778
Probability	0.0000	0.0000
Observations	1487.0000	1487.0000

Figure 1. Volatility clustering of Composite Bank Sector

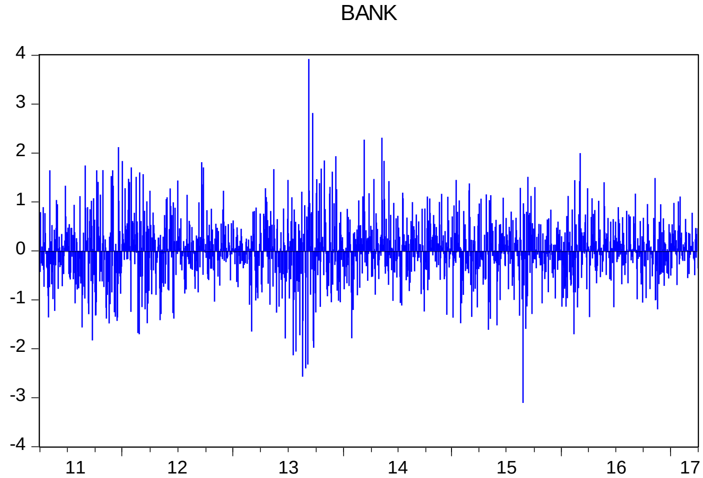
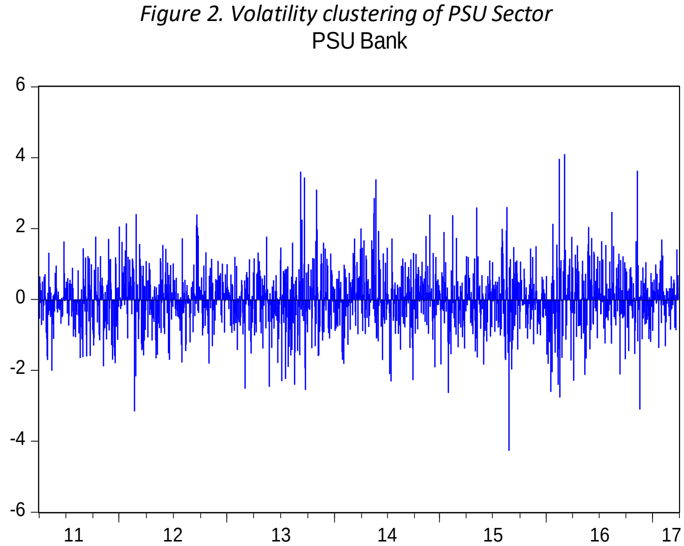


Figure 1 and 2 makes it clear that volatility clustering can be observed where large changes are followed by large changes and small changes followed by small changes.

Figure 2. Volatility clustering of PSU Sector



Both sectors are showing more peaked spikes or high volatility in 2013 and 2015.

2. ADF unit root test

In Table 2 ADF test results are shown it can be seen that both sectors returns are stationary at levels with constant and trend. **H0** = y contains unit root or non-stationary. **H1**= y is stationary. The series should be stationary to apply EGARCH model. Both sectors absolute t-statistics is greater than MacKinnon critical values. So the H0 of unit root or non-stationary series get rejected resulting both series are stationary.

Table 2. Augmented Dickey-Fuller (ADF) unit root test

Data	Indices	At Level	
		t-statistics	P-value
Daily Data	Bank	-34.75307	0.000
	PSU Bank	-35.41998	0.000
	Test critical values **	1% level	-3.964232
		5% level	-3.412837
		10% level	-3.128403

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

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3. Modelling of mean equation

We have modelled the mean equation through AR (1) Autoregressive Process with constant. Residuals are obtained from mean equation. Residuals are checked for auto correlation by using Ljung box Q statistics. Autocorrelation has been checked up to 36 lags but results are shown up to 5 lags. Table 3 is showing residuals diagnostics. We can see that there has no autocorrelation in residuals of both sectors because p>0.01 for all 5 lags. But at lag 2 and 3 at 5% level in Bank sector there is autocorrelation. After this squared residuals are checked for serial correlation and it can be seen that Null hypothesis of no autocorrelation get rejected because all p<0.01 and 0.05 indicating serial correlation in squared residuals. After this ARCH effect is checked up to lag two. It can be seen that all p<0.01 and 0.05 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 3 we can ensure to proceed for EGARCH (1, 1) model.

Table 3. Residual diagnostics

	Residual series					Squared residual series				
Sectors	lags	AC	PAC	Q-stat	P-value	lags	AC	PAC	Q-stat	P-value
	1	0.007	0.007	0.068	-	1	0.077	0.077	8.807	0.003
	2	-0.062	-0.062	5.774	0.016	2	0.129	0.124	33.712	0.000
Bank	3	0.022	0.023	6.495	0.039	3	0.031	0.013	35.156	0.000
	4	-0.029	-0.033	7.708	0.052	4	0.026	0.007	36.172	0.000
	5	-0.012	-0.009	7.937	0.094	5	0.040	0.033	38.546	0.000
	1	0.000	0.000	0.000	-	1	0.103	0.103	15.759	0.000
	2	0.001	0.001	0.003	0.955	2	0.039	0.028	17.971	0.000
PSU Bank	3	0.019	0.019	0.528	0.768	3	0.078	0.072	26.939	0.000
	4	-0.024	-0.024	1.417	0.702	4	0.058	0.043	32.035	0.000
	5	-0.021	-0.021	2.080	0.721	5	0.057	0.043	36.853	0.000

ARCH LM Test

Sectors	lags	F- stat.	P-value	obs R- squared	P-value	Inference
Bank	1	8.825	0.003	8.785	0.003	ARCH effect
	2	16.075	0.000	31.530	0.000	ARCH effect
PSU Bank	1	15.866	0.000	15.719	0.000	ARCH effect
	2	8.515	0.000	16.870	0.000	ARCH effect

4. EGARCH model results

In Table 4 it can be seen that ARCH and GARCH coefficients of variance equations are significant and positive in both sectors. Significant and positive value of ARCH Term (α_1) 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 (β_1) indicates present volatility or conditional variance is significantly affected by previous period conditional variance.

Table 4. EGARCH (1, 1) model results

Particulars	Coefficients	Bank	P-values	PSU Bank	P-values
Mean Equation	α_0	0.0101	0.5205	-0.0088	0.6929
	AR Term (β_1)	0.0852	0.0007*	0.0762	0.0030*
Variance Equation	Constant (α_0)	-0.0669	0.0001*	-0.1086	0.0002*
	ARCH Term (α_1)	0.0730	0.0004*	0.1224	0.0002*
	GARCH Term (β_1)	0.9867	0.0000*	0.9487	0.0000*
	Leverage Term (γ)	-0.0661	0.0000*	-0.0264	0.1161
	α1+β1 of Variance Equation	1.0597		1.0711	
Durbin Watson Stat.		1.9517		1.9832	
Log Liklihood		-1350.5030		-1842.0600	
Akaike info criterion		1.8271		2.4886	
Schwarz criterion		1.8520		2.5136	

*(Note - * values indicate significant p values at 5%)*

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β_1 Values are close to one in both sectors indicating higher persistence of shocks of volatility.$\beta_1$value in bank sector is higher than PSU bank means volatility persists more in Bank sector. 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 while in PSU Bank sector Leverage term coefficient is negative but insignificant indicating absence of leverage effect. Sum of $\alpha1$ and $\beta1$is greater than one in both sectors 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 4 it can be observed that Durbin Watson statistics is near to two indicating no autocorrelation after implementation of EGARCH model. From Table 5it can be observed that there is no ARCH effect remained in both sectors at lag one or two.

Table 5. EGARCH Model residual diagnostic

EGARCH(1,1)						
Indices	lags	F- statistics	P-value	obs R- squared	P-value	Inference
Bank	1	0.1415	0.7068	0.1417	0.7066	No ARCH
	2	0.0763	0.9266	0.1528	0.9264	No ARCH
PSU Bank	1	1.1023	0.2939	1.1029	0.2936	No ARCH
	2	0.7409	0.4769	1.4832	0.4763	No ARCH

Table 6 displays parameters of EGARCH model. α_1 values are higher in PSU banks indicating returns are more spiky means movements of this Index prices is higher than Bank sector index. β_1 values are higher in Bank sector indicating volatility persist slight more in this sector as compared to PSU bank. γ values is higher in PSU bank indicating this sector volatility is more prone to negative news as compared to Bank sector.

Table 6. Parameter of EGARCH model

EGARCH	α_1(Spikes)	β_1(persistence)	γ(leverage effect)
Bank	0.0730	0.9867	-0.0661
PSU Bank	0.1224	0.9487	-0.0264

5. Conclusion

This study is related to analyse the volatility of two sectors namely composite Bank sector and PSU bank sector of National Stock Exchange, India from April 2011 to March 2017 with the help of EGARCH model. It is analysed that distribution of both 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 both 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.$\beta_1$values are close to one in both sectors indicating higher persistence of shocks of volatility, shocks takes longer time to die out. Volatility persists slight more incomposite Bank sector than PSU bank sector. Negative and significant leverage term coefficient in both sectors indicates presence of leverage effect means negative shocks have larger impact on volatility than positive shocks; PSU Bank sector volatility is more prone to negative news compared to composite Bank sector. Composite Bank sector includes private banks also that's why it may be possible that private banks performance minimise the negative shocks impact but shocks takes time to die out in composite Bank sector also.Sum of $\alpha1$ and $\beta1$is greater than one in both 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 both sectors have heterogeneous responses towards volatility so requires attention but PSU bank sector requires more 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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