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Leverage Effect in Indian Banking Sector Returns

Vandana Dangi*

Abstract

Indian banking industry has emerged as a reliable investment alternative among investors. Rational investors rely on fundamental analysis while taking decision regarding investing their moneyin banking sector. They estimate and predictreturn alongside risk in fundamental analysis of an investment avenue in banking sector. The prediction of impact of negative or positive news on volatility in banking stocks is also vital for investors to measure the risk exposure in their investment. The present treatise is an attempt to investigate the leverage effect in Indian banking sector indices ofBSE Bankex, CNX bank and CNX PSU. The daily banking sector indices for the period of January 2004 to October 2014 are taken from the online database maintained by the Bombay Stock Exchange Ltd. and the National Stock Exchange Ltd. The banking sector return series are initially studied for stationarity with the help of Augmented Dickey–Fuller test. The return series are further tested for autoregressive conditional heteroskedasticity (ARCH)with the help of Engle's ARCH test (i.e Lagrange multiplier test) and Breush-Godfrey-Pagan test. The test results confirmed that the return series are stationary and ARCH effect is present in return series. Vanilla GARCH model do not allow for asymmetries. So, EGARCH model was employed to study the leverage effectinBSE Bankex,CNX bank and CNX PSU return series. The results confirm the presence of highly persistent volatility and asymmetric leverage effect in banking sector return series. The conditional variance reacts differently to a given positive shock than to a negative shock with equal magnitude. The news impact curvesdrawn from EGARCH fitted series indicate that investors would face higher uncertainty in negative shocks as compared to positive shocks. These results will help investors in framing their strategy for risk management.

Keywords: Asymmetries, autoregressive conditional hetroskedasticity, news impact curve, stationarity and volatility clustering

* Assistant Professor, Government College, Badli, Delhi; vandanashoora@yahoo.com

1. INTRODUCTION

Indian banking sector have significantly developed in terms of transparency and efficiency. The credit of its improvement goes to the timely introduced reforms that include the enactment of the Securitization Act, establishment of asset reconstruction companies, change in the basis of income recognition, initiatives for improving recoveries from non-performing assets and regulatory uniformity in Indian banking sector. These developments on one hand spurted the treasury income and on other hand improved the loan recoveries of Indian banks. The outstanding track record of innovation, growth and value creation is reflected in their market valuation. Indian banking sector has emerged as one of the most attractive investment avenues for investors not only for depositing their money but also to invest their money in their securities. Masses sacrifice their present benefits in order to earn future benefits after analysing the market by employing technical analysis or/and fundamental analysis. The prediction of volatility in financial market is vital for investors as it indicates a measure of risk exposure in their investment. Investors need to study the behaviour of volatility in response to the news. They need to find either the return series have symmetrical response or asymmetrical response to different kind of news. So, investors study the impact of news on volatility in banking stocks. News about government policies, political unrest, financial results, global cues, mergers and acquisitions, Foreign Institutional Investors activities, insider trading, bonus dividends, stock splits, inclusion/exclusion from indexes, rights issue, change in board, changes in demand or/and supply, joint ventures, rumors, new technology, new interventions and many more affects stock markets as these factors have a direct impact on the bank indices. Investors analyse the relationship between the news and the market because news can change a good day into bad one or bad day into a good. That is why; the accurate modeling and forecasting of the volatility and the impact of news have received a lot of attention in the investment community. The introduction of ARCH models by Engle (1982) and their generalization by Bollerslev (1986) had refined the approach to model the conditional volatility that captures the stylized characteristics of the financial data in better way. Crouhy Michel and Rockinger Michael (1997) applied AT-GARCH (1,1) model to capture the residual structure by extending ATGARCH (1,1) to an hysteresis model (HGARCH) for structured memory effects. They found that bad news was discounted very speedily in volatility. However, good news had a very small impact on the volatility. Robert A. Connolly and Christopher T. Stivers (1999) studied variations in the volatility relation between the conditional variance of individual firm returns and yesterday's market return shock by using daily equity returns. They found number of regularities in this market-to-firm volatility relation. They concluded that volatility decreases following macroeconomic news announcements. Volatility did not change systematically during the high-news months when firms announce quarterly earnings. Kaur, Harvinder (2004) employed various volatility estimators and diagnostic tests to investigate the nature and characteristics of volatility in the Indian stock market. She found that volatility clustering, asymmetry, intra-week and intra-year seasonality, spillover between the US and Indian markets were present in Sensex and Nifty. Connolly, Robert A. and Stivers, Christopher Todd (2005) studied volatility behaviour in the daily stock returns at index and firm level from 1985 to 2000. They noticed decline in the relation between a day's index return shock to its next period's volatility when important macroeconomic news was released. They finally concluded that volatility clustering was strong when there were disperse beliefs about the market's information signal. Bhaskar Sinha (2006) modelled the presence of volatility in the inter day returns in the Sensex of the Bombay Stock Exchange and the Nifty of the National Stock Exchang e. He employed asymmetric GARCH family of models to unearth the phenomena of volatility clustering and persistence of shock in these two indices. They concluded that EGARCH and GJR-GARCH model successfully explain the conditional variance in the returns from Sensex (BSE) and Nifty (NSE) respectively. Pati, Pratap

Chandra (2006) examined the volatility dynamics and investigated the Samuelson Maturity Hypothesis in the context of Indian Futures Market by using ARMA-GARCH, ARMA-EGARCH models. He took Nifty Index Futures daily closing price, volume and open interest traded on NSE from the period January 1, 2002 to December 29, 2005 for near month contract. He found time-varying volatility, volatility clustering and leverage effect in Indian futures market. Sarangi, Sibani Prasad and Patnaik, K. Uma Shankar (2006) used family of GARCH techniques to capture time varying nature of volatility and volatility clustering in the returns of S&P CNX Nifty, Nifty Junior and S&P 500 index from January 1, 1997 to March 31, 2005. They found that there were no significant changes in the volatility of the spot market of the S&P CNX Nifty Index but there was change in the structure of the volatility to some extent. They also found that the new information was assimilated into prices more rapidly than before indicating decline in the persistence of volatility in the indexes since the inception of futures trading. Daal Elton, Naka Atsuyuki and Yu Jung-Suk (2007) proposed a mixed GARCH-Jump model for the specific circumstances in emerging equity markets. They accommodated lagged currency returns as a local information variable in the model. The lagged currency returns in the autoregressive jump intensity function incorporated jumps in the returns and volatility. Their proposed model encompasses asymmetrical volatility response to both normal innovations and jump shocks. Model captured the distinguishing characteristics of the Asian index returns and significantly improved the fit for markets that were affected by Asian crisis in 1997. Hourvouliades, L.Nikolaos (2007) examined the existence and nature of volatility clustering in the Athens FTSE20 index futures contract to unearth the characteristics of clustering in derivatives market. He applied GARCH model and exponential smoothing model to compare forecasting power on volatility. He found volatility clustering in the time series of the Greek futures market with negative shocks being more persistent as compared to positive shocks. Ninga Cathy, Xub Dinghai and Wirjantoc Tony S (2009) investigated the asymmetric pattern of volatility clustering on both the foreign exchange rate and stock markets. They employed copula-based univariate time-series models that accommodate the clusters of both small and large volatilities. They concluded that the volatility clustering was strongly asymmetric in the sense that clusters of large volatilities tend to be much stronger than clusters of small volatilities. They further concluded that the volatility clusters remain persistent even after forty days. Ramlall Indranarain (2010) studied the impact of the credit crunch on the volatility clustering and leverage effects in major international stock markets. He studied the impact with GARCH (1, 1), GJR and news impact curves techniques. He found that GARCH fits all the stock markets except for SEMDEX. He noticed leverage effects in the post crisis period only in case of emerging markets such as JSE and SSEC. He concluded that the credit crunch accentuated the level of volatility clustering and also increased leverage effects in major international stock markets. Mahmud, Mahreen and Mirza, Nawazish (2011) modelled and forecasted the volatility before and during the financial crisis in the stocks traded at the KSE (Karachi Stock Exchange). They found volatility clustering and asymmetries in the return series. They applied GARCH family of models capability of the EGARCH(1,1) model at forecasting for both periods lending support to the use of GARCH family of models for emerging markets during crisis. Sinha, Bhaskar (2012) modelled the volatility by using GARCH family models in the historical returns of Sensex and Nifty to find volatility clustering and persistence of shock. He found that EGARCH and GJR-GARCH model successfully modelled the Sensex data Nifty data respectively. Xue Yi and Gencay Ramazan (2012) studied multiple trading frequencies using Bayesian information updates in an incomplete market and introduced a market microstructure model to generate volatility clustering with hyperbolically decaying autocorrelations. They concluded that signal extraction induced by multiple trading frequencies can increase the persistence of the volatility. They found that the volatility of the underlying returns series varies greatly with the number of traders in the market. Lin, Pin-te and Fuerst, Franz (2013) applied a Lagrange multiplier test for the autoregressive conditional heteroskedasticity effects and an exponential generalized autoregressive conditional heteroskedasticity-in-mean model to assess the similarity financial characteristics of regional house prices and stock indices in Canada. They found that volatility clustering, positive risk-return relationships and leverage effects exist in the majority of provincial housing markets of Canada. They further concluded that volatility behaviours differ across provinces. More densely populated provinces as compared to less populated provinces exhibited stronger volatility clustering of house prices.

Academicians and researchers have given lot of attention to the volatility dynamics and impact of news in the developed and emerging financial markets. But there is lack of investigation of leverage effect in the sectoral indices of banking sector in India. The present treatise is an attempt to fill this lacuna by exploring the leverage effect in Indian banking sector indices of two largest stock exchanges of India.

2. OBJECTIVE OF THE STUDY

The present treatise attempts to study the leverage effect in Indian banking sector indices of BSE Bankex, CNX bank and CNX PSU by estimation of market volatility in terms of asymmetrical response to news.

3. RESEARCH METHODOLOGY

The daily stock price data for the period of January 2004 to October 2014 on BSE Bankex, CNX bank and CNX PSU have been taken from the online database maintained by the Bombay Stock Exchange Ltd. (BSE) and the National Stock Exchange Ltd. (NSE). The present treatise attempts to investigate the leverage effects in three Indian banking indices. It covers the two leading banking indices of BSE and NSE viz. BSE Bankex and CNX bank. There have been various changing dynamics of Indian banking industry. Public sector banks play dominant role in Indian banking sector. Public sector banks hold more than sixty seven per cent of total assets of all scheduled commercial banks. So, the present treatise also covers one public sector indices of NSE viz. CNX PSU.

Bankex indices track the performance of banking sector stocks listed on the Bombay Stock Exchange Ltd. It includes the stocks of UTI Bank Ltd, Kotak Mahindra Bank, UCO Bank, Indian Overseas Bank, Jammu & Kashmir Bank, Vijaya Bank, Allahabad Bank Ltd, Centurion Bank Ltd, Indusind Bank Ltd, Karnataka Bank Limited, Federal Bank Ltd, Yes Bank Ltd, IDBI Bank Ltd. These stocks represent ninety percent of the total market capitalization of all banking sector stocks. This index is based on the free float methodology of index construction. The other index is CNX Bank Index. This index is comprised of the large capitalised and most liquid Indian banking stocks. It includes twelve stocks from the banking sector that trade on the National Stock Exchange Ltd. It is computed using free float market capitalization method. This index represents fourteen percent of the free float market capitalization of the stocks listed on NSE. The top ten constituents as per their weightage in the index are HDFC Bank Ltd. (30.52), ICICI Bank Ltd. (28.42), State Bank of India (11.60), Axis Bank Ltd. (8.71), Kotak Mahindra Bank Ltd. (7.16), IndusInd Bank Ltd. (4.36), Bank of Baroda (2.58), Yes Bank Ltd. (2.15), Punjab National Bank (1.91) and Bank of India (0.94). CNX PSU index consists of major public sector banks that are listed on National Stock Exchange Ltd. CNX PSU index again comprises of twelve companies listed on National Stock Exchange Ltd. It is computed using free float market capitalization weighted method. The top ten constituents as per their weightage in the index are State Bank of India (54.48), Bank of Baroda (12.13), Punjab National Bank (8.99), Bank of India (4.42), Canara Bank (4.14), Union Bank of India (3.61), IDBI Bank Ltd. (2.88), Oriental Bank of Commerce (2.32), Allahabad Bank (2.23) and Syndicate Bank (1.80).

4. ECONOMETRIC METHODOLOGY

The present treatise uses the log difference of closing prices of two successive periods in order to calculate the rate of return as the volatility in BSE Bankex, CNX bank and CNX PSU indices has been estimated on return. The log difference is expressed in percentage terms that ease comparability. The series of banking sector indices have been converted into return series by applying the following formula:

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

where R_t is the return for day t, p_{t-1} is closing prices for day t, is the closing prices of previous trading day and *ln* is natural log.

The data was initially studied for stationarity with the help of **Augmented Dickey–Fuller test.** It is a test for a unit root in a time series sample. It examines whether a time series variable is non-stationary using an autoregressive model. It tests the existence of a unit root as the null hypothesis. The testing procedure for the ADF test consists of estimating the following regression:

$$\Delta y_t = \square + \beta t + \gamma y_{t-1} + \delta\_1\ \Delta y_{t-1} + \ldots + \delta_{p-1}\ \Delta y_{t-p+1} + \varepsilon_t \quad (2)$$

The unit root test is carried out under the null hypothesis against the alternative hypothesis of Once a value for the test statistic is computed, it is compared to the relevant critical value for the Dickey–Fuller Test. If the test statistic is less than the critical value, then the null hypothesis is rejected implying no unit root is present.

The data is further tested for autoregressive conditional heteroskedasticity with the help of **Engle's ARCH test (i.e Lagrange multiplier test) and Breush-Godfrey-Pagan test.** The ordinary least square equation may mislead in case of time varying variance. The residuals from the ordinary least square regression equation is tested for Autoregressive Conditional Heteroskedasticity effect (ARCH effect) to verify either the assumption of constant variance holds good or it is time varying. Engle's ARCH test is a Lagrange multiplier test to assess the significance of ARCH effects. The null hypothesis is:

$$a_0 = a_1 = \ldots = a_m = 0 \quad (3)$$

The alternative hypothesis is:

$$e_t^2 = a_0 + a_1 e_{t-1}^2 + \ldots + a_m e_{t-m}^2 + u_t \quad (4)$$

where u_t is a white noise error process.

Breush-Godfrey-Pagan test is based on the Lagrange multiplier test principle (John H.H. Lee, 1991) that is used to test heteroskedasticity in the regression model. It is a chisquared test with k degrees of freedom. It examines whether the estimated variance of the residuals are dependent on the independent variable. The heteroskedasticity is examined by regressing the squared residuals on the independent variables:

$$\hat{u}^2 = Y_0 + Y_1\ x + \upsilon \quad (5)$$

5. MODEL SPECIFICATION

Models can be linear in mean and variance (like ARMA model); linear in mean and non-linear in variance (like Generalised Autoregressive Conditional Heteroskedasticity Model); non-linear in mean and linear in variance (like Bicorrelation Model); and non-linear in mean and non-linear in variance (like Threshold GARCH Model). Linear models are incapable to explain leptokurtosis, volatility clustering and leverage effect. The appropriateness of a non-linear model for the data may be judged on the statistical ground. Generalised Autoregressive Conditional Heteroskedasticity (GARCH) type process best characterised the dependence (Brooks 1996). Engle (1982) had proposed ARCH process to model time varying conditional variance by using past disturbances. He used past disturbances to model the variances of the series and allow the variance of the error term to vary over time. Bollerslev (1986) further generalized the ARCH process. GARCH model avoid over fitting and it is more parsimonious. This model allows infinite number of past errors to effect current conditional variance. As already discussed, GARCH model cannot account for the leverage effects as it is unable to allow for direct feedback between the conditional mean and conditional variance. The conditional variance in the model is not the function of signs of lagged residuals rather it is the function of magnitude of lagged residuals. That is why, GARCH model enforce a systematic response to positive and negative shocks. The Nelson's (1991) Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) model allows asymmetries as log(is modelled and there is no need for artificially imposing the non-negativity constraints for the model parameters. The conditional variance is modelled to capture the leverage effect of volatility. The EGARCH(1,1) model is defined as follows:

$$In\ (h^2_t)=0+\gamma\ (e_{t-1}/h_{t-1})+\ \lambda\ [(|e_{t-1}\ |/h_{t-1})-(\square 2/\pi)^{0.5}]+\ \beta In\ (h^2_{t-1}) \quad (6)$$

Where () is conditional variance

γ , and β are parameters

represents the symmetric effect i.e. GARCH effect

β measures the persistence level in conditional volatility

γ measures the leverage effect

If the value of $\gamma = 0$, then it indicates that the model is symmetric. In case $\gamma < 0$, then good news generate less volatility than bad news. When $\gamma > 0$, it indicates that good news are more destabilizing than bad news.

Properties of BSE Bankex, CNX bank and CNX PSU Market Returns

Daily closing prices have been taken for BSE Bankex, CNX bank and CNX PSU. These price series are converted to return series. The basic statistics of BSE Bankex, CNX bank and CNX PSU return series are portrayed in the table 1.

Table 1: Basic statistics of BSE Bankex, CNX bank and CNX PSU returns

Descriptive Statistics	BSE Bankex	CNX bank	CNX PSU
Mean	0.071413	0.069110	0.049050
Median	0.119154	0.091396	0.114867
Maximum	17.54832	17.23940	16.35230
Minimum	-14.48036	-15.13805	-17.19390
Std. Dev.	2.081732	2.114401	2.267583
Skewness	-0.058808	-0.122066	-0.207368
Kurtosis	8.640934	8.443158	7.459534
Jarque-Bera	3561.426	3321.297	2244.151
Probability	0.000000	0.000000	0.000000
Observations	2685	2685	2685

The average statistics of BSE Bankex, CNX bank and CNX PSU returns are positive implying the fact that all indices have increased over the period. The returns are negatively skewed that indicates the high probability of earning negative returns. The value of kurtosis statistics is more than three. It means that the data is leptokurtic. BSE Bankex, CNX bank and CNX PSU returns series have a heavier tail as compared to the standard normal distribution. Jarque-Bera test confirms the non-normality of all return series of Indian banking sector as the value of probability is zero i.e. the null hypothesis of normal distribution cannot be accepted by the Jarque-Bera test.The return series of BSE Bankex, CNX bank and CNX PSU are tested for stationarity by applying Augmented Dickey–Fuller test.

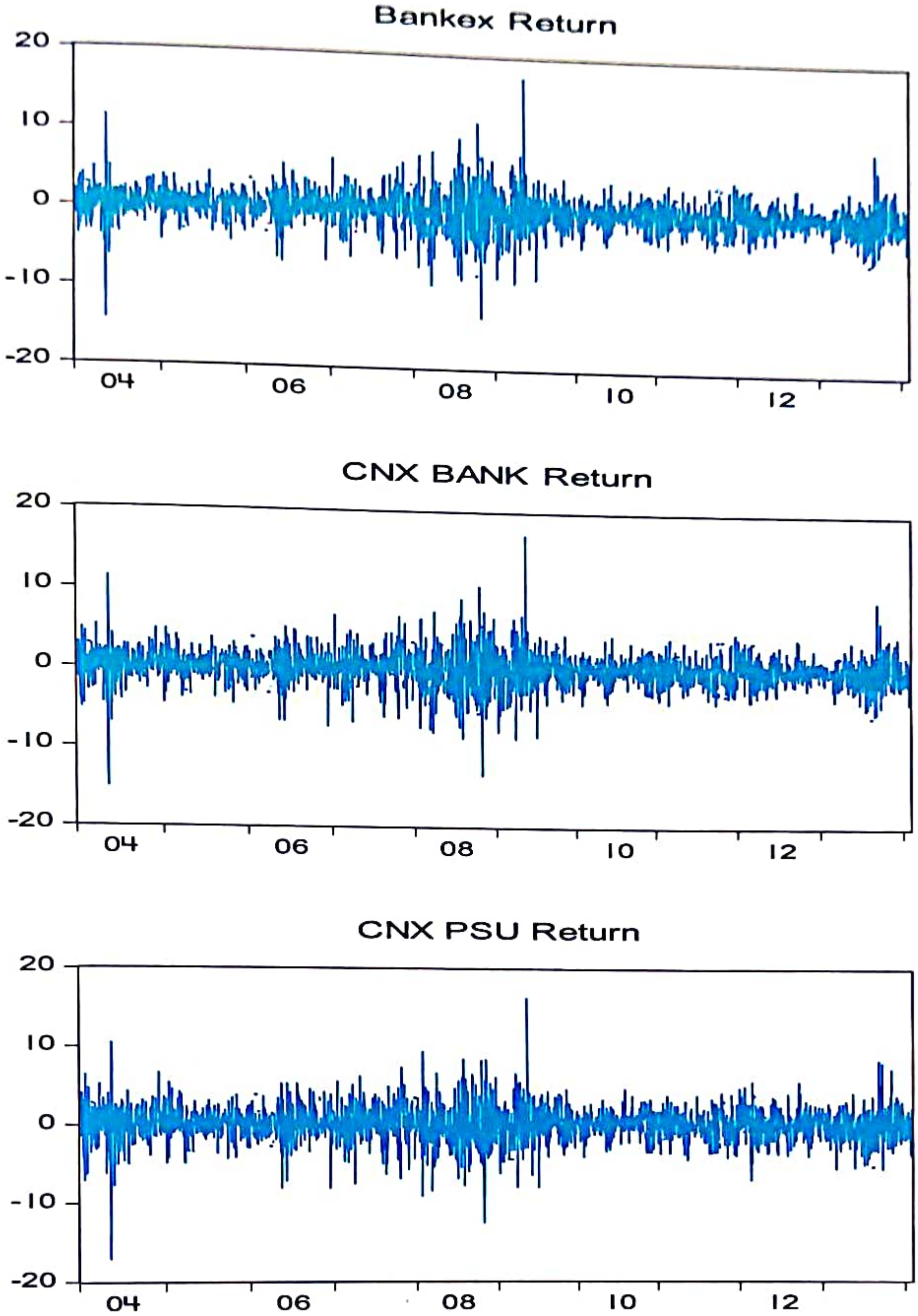
Table 2: Results of augmented Dickey–Fuller test

Panel	Null Hypothesis	t-Statistic	Prob.*
1	BANKEX has a unit root	-45.17067	0.0000
2	CNXBANK has a unit root	-45.16801	0.0000
3	CNXPSU has a unit root	-45.09170	0.0000

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

The results of Augmented Dickey–Fuller test in table 2 indicate that all return series are stationary. The null hypothesis that the returns series have unit root is rejected as the probability value is 0 i.e. less than 0.05. Exhibit 1 portrays the daily returns on BSE Bankex, CNX bank and CNX PSU returns series. It is clear from the visual inspection that volatility in banking sector indices has changed over time. There are clear and distinct periods of high volatility and relative calm that suggests volatility clustering in the BSE Bankex, CNX bank and CNX PSU indices. Returns on BSE Bankex, CNX bank and CNX PSU indices continuously fluctuate around a mean value that is close to zero.

Exhibit 1: Plot of daily returns



Box-Jenkins methodology is applied to detect whether BSE Bankex, CNX bank and CNX PSU return series follow a pure AR process or pure MA process or ARMA process. The results shown in table 3 and 4 specifies ARMA (1,1) structure of the mean equation for BSE Bankex, CNX bank and CNX PSU return series.

Table 3: Correlogram of return series of BSE Bankex, CNX bank and CNX PSU

	Bankex		CNX bank		CNX PSU	
Lags	AC	PAC	AC	PAC	AC	PAC
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						

Table 4: Results of ACF, PACF and Q statistics

	Bankex				CNX bank				CNX PSU			
Lags	AC	PAC	Q-stat	Prob	AC	PAC	Q-stat	Prob.	AC	PAC	Q-stat	Prob
1	0.136	0.136	49.53	0	0.136	0.136	49.571	0	0.138	0.138	51.449	0
2	-0.031	-0.05	52.115	0	-0.035	-0.055	52.913	0	-0.027	-0.047	53.369	0
3	-0.005	0.006	52.192	0	-0.01	0.003	53.16	0	-0.003	0.007	53.397	0
4	-0.024	-0.026	53.698	0	-0.02	-0.021	54.232	0	0	-0.002	53.397	0
5	-0.051	-0.045	60.768	0	-0.055	-0.05	62.268	0	-0.049	-0.05	59.987	0
6	-0.059	-0.048	70.008	0	-0.056	-0.044	70.574	0	-0.04	-0.026	64.284	0
7	-0.003	0.008	70.026	0	0.002	0.011	70.583	0	0	0.006	64.285	0
8	0.037	0.032	73.662	0	0.028	0.022	72.701	0	0.015	0.012	64.9	0
9	0.031	0.02	76.189	0	0.032	0.025	75.516	0	0.045	0.043	70.428	0
10	0.028	0.02	78.275	0	0.029	0.02	77.736	0	0.031	0.018	73.025	0
11	0.023	0.014	79.704	0	0.022	0.013	79.004	0	0.007	0	73.168	0
12	-0.007	-0.011	79.825	0	-0.006	-0.01	79.106	0	-0.013	-0.013	73.615	0
13	-0.007	0.001	79.966	0	-0.008	0	79.281	0	-0.014	-0.009	74.108	0
14	0.033	0.04	82.832	0	0.032	0.039	82.06	0	0.036	0.044	77.68	0
15	0.008	0.003	83.002	0	0.008	0.003	82.243	0	0.017	0.011	78.5	0

The estimates of obtained from usual ordinary least square are linear, unbiased and asymptotically normally distributed in large samples but they are not efficient in comparison to other linear and unbiased estimates in the presence of hetroscedasticity and autocorrelation. Although the pictorial representation of return series indicates the clustering but Engle's ARCH test and Breush-Godfrey-Pagan test are further applied in the ARMA model to test the persistence and predictability of volatility in the Indian banking sector. The most common Durbin Watson test to detect autocorrelation is inapplicable in these autoregressive models. So, the residuals are tested for ARCH effect and the results of the same are displayed in table 5 and 6.

Table 5: Results of Engle's ARCH test

PANEL 1: BANKEX			
F-statistic	164.6013	Prob. F(1,2500)	0.0000
Obs*R-squared	155.1957	Prob. Chi-Square(1)	0.0000
PANEL 2: CNXBANK			
F-statistic	203.6823	Prob. F(1,2500)	0.0000
Obs*R-squared	189.4418	Prob. Chi-Square(1)	0.0000
PANEL 3: CNXPSU			
F-statistic	267.7342	Prob. F(1,2500)	0.0000
Obs*R-squared	242.0286	Prob. Chi-Square(1)	0.0000

Table 6: Results of Breusch-Godfrey Serial Correlation LM Test

PANEL 1:BANKEX			
F-statistic	0.058082	Prob. F(2,2679)	0.9436
Obs*R-squared	0.116357	Prob. Chi-Square(2)	0.9435
PANEL 2: CNXBANK			
F-statistic	0.204653	Prob. F(2,2679)	0.8149
Obs*R-squared	0.409987	Prob. Chi-Square(2)	0.8147
PANEL 3: CNXPSU			
F-statistic	1.208119	Prob. F(2,679)	0.2989
Obs*R-squared	2.418536	Prob. Chi-Square(2)	0.2984

Engle's ARCH test confirms the presence of conditional heteroskedasticity in the return series of BSE Bankex, CNX bank and CNX PSU as the probability value is zero. The results of Breush-Godfrey-Pagan test in table 6 also confirm that the estimated variance of the residuals is dependent on the independent variable as the probability value is more than 0.05.

6. LEVERAGE EFFECT: ESTIMATION OF MARKET VOLATILITY IN TERMS OF ASYMMETRICAL RESPONSE TO NEWS

The differential response to good or bad news leads to the asymmetric response to the various shocks. It is also known as leverage effects. EGARCH model is estimated on the BSE Bankex, CNX bank and CNX PSU return series in order to test the significance of the asymmetric effects. The leverage effect in the EGARCH model is not quadratic but exponential. So, the forecast of conditional variance is non negative. Table 7, 8 and 9 portrays the results of EGARCH model estimation.

Table 7: EGARCH model estimation on BSE BANKEX returns series

Dependent Variable: RBANKEX

Method: ML - ARCH (Marquardt) - Normal distribution

Convergence achieved after 22 iterations

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5) *RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	-0.013520	0.014462	-0.934905	0.3498
C	0.128898	0.049842	2.586155	0.0097
Variance Equation				
C(3)	-0.106211	0.009494	-11.18664	0.0000
C(4)	0.173541	0.013684	12.68235	0.0000
C(5)	-0.057241	0.006854	-8.351162	0.0000
C(6)	0.978028	0.003301	296.2777	0.0000
Log likelihood	-5404.338	Akaike info criterion		4.030047
Durbin-Watson stat	1.731525	Schwarz criterion		4.043221

The uppersection in table 7 provides the output for mean equation and the lower section contains the coefficients, z statistics and prbability value of the coefficients of the variance equation. The value of EGARCH parameter is close to one. It implies that volatility shocks are persistent. The leverage effect term i.e C(5)*RESID(-1)/@SQRT(GARCH(-1)) in model is negative. It is significantly different from zero that proves that news impact is assymetric during the sample period. In other words, leverage effcet exists for the BSE Bankex return series during the sample period.

In CNX BANK return series also, the value of EGARCH parameter is close to one. It implies that volatility shocks are persistent. The leverage effect term i.e C(5)*RESID(-1)/@SQRT(GARCH(-1)) in model is also negative in table 8. It is significantly different from zero that proves that news impact is assymetric. In other words, leverage effcet exists for the CNX BANK return series during the sample period.

Table 8: EGARCH model estimation on CNX BANK returns series

Dependent Variable: RCNXBANK
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1/02/2004 10/31/2014
Included observations: 2685 after adjustments
Convergence achieved after 23 iterations
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	-0.011526	0.014912	-0.772947	0.4396
C	0.130823	0.053972	2.423901	0.0154
		Variance Equation		
C(3)	-0.101871	0.009442	-10.78923	0.0000
C(4)	0.169077	0.013521	12.50432	0.0000
C(5)	-0.054132	0.006732	-8.041220	0.0000
C(6)	0.978081	0.003412	286.6892	0.0000
Log likelihood	-5477.869	Akaike info criterion		4.084819
Durbin-Watson stat	1.730459	Schwarz criterion		4.097993

Table 9: EGARCH model estimation on CNX PSU returns series

Dependent Variable: RCNXPSU
Method: ML - ARCH (Marquardt) - Normal distribution
Sample (adjusted): 1/02/2004 10/31/2014
Included observations: 2685 after adjustments
Convergence achieved after 26 iterations
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	-0.009493	0.017435	-0.544481	0.5861
C	0.112079	0.077794	1.440702	0.1497

Variance Equation				
C(3)	-0.078780	0.008900	-8.851975	0.0000
C(4)	0.187760	0.014449	12.99481	0.0000
C(5)	-0.039239	0.007423	-5.286024	0.0000
C(6)	0.957129	0.005800	165.0200	0.0000
Log likelihood	-5808.534	Akaike info criterion		4.331124
Durbin-Watson stat	1.721889	Schwarz criterion		4.344299

The value of EGARCH parameter in the model estimation of CNX PSU returns series is close to one in table 9. It implies that volatility shocks are persistent in CNX PSU returns series. The leverage effect term i.e C(5)*RESID(-1)/@SQRT(GARCH(-1)) in the model is also negative. It is significantly different from zero that proves that news impact is assymetric during the sample period. In other words, leverage effect exists for the CNX PSU returns series during the sample period. Table 10 portrays the value of log liklihood, Akaike info criterion and Schwarz criterion for the estimates of GARCH(1,1) model.

Table 10: Criterion of GARCH(1,1) Model

Criterion	BSE Bankex	CNX bank	CNX PSU
Log likelihood	-5392.347	-5470.556	-5784.413
Akaike information criterion	4.022673	4.080891	4.314764
Schwarz criterion	4.035791	4.094069	4.327942

A peculiar point to here is that the log liklihood in EGARCH model estimation for all series is higher than the estimates of GARCH(1,1) model. The Akaike info criterion and Schwarz criterion are lower in EGARCH model estimation as compared to GARCH(1,1) model. So, EGARCH model performs better results as compared to GARCH model.

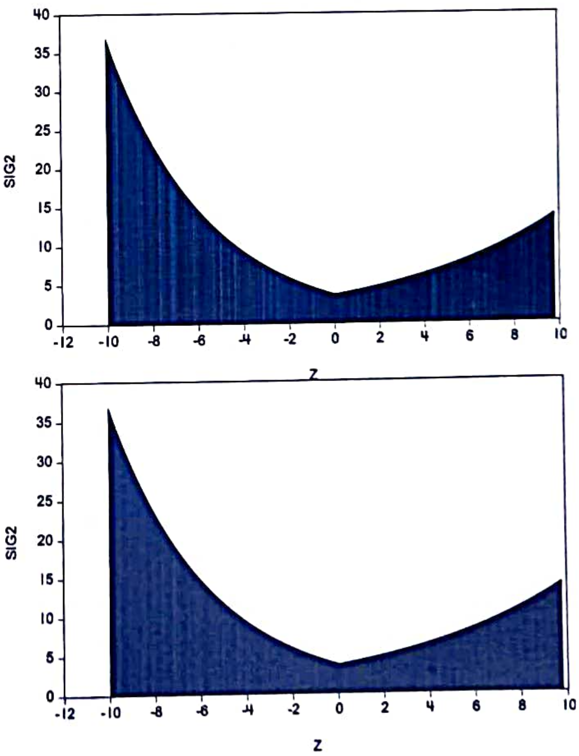
News Impact Curve

The news impact curve plots the volatility as against the impact (i.e. $z=\varepsilon/\sigma$) where

$$\log \sigma_t^2 = \omega + \beta \log \sigma^2_{t-1} + \alpha |Z_{t-1}| + YZ_{t-1} \qquad (7)$$

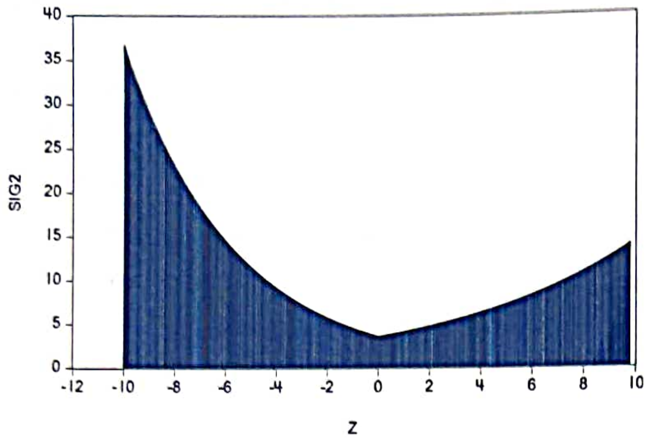
Initially, last period's volatility is fixed and then one period impact is estimated which is conditional on the last period's volatility. The next step is to generate the conditional variance series. The x axis of news impact curve is z series that is generated as a equispaced period between -10 and +10. The variance series is generated that is named as SIG2. Finally, news impact curves are estimated by highlighting the z series and SIG2 series from EGARCH model fitted to the BSE Bankex, CNX bank and CNX PSU return series. Exhibit 2 plots the news impact curve for the BSE Bankex, CNX bank and CNX PSU return series.

Exhibit 2: News Impact Curve From EGARCH Estimations



A) BSE Bankex return series

B) CNX bank return series



C) CNX PSU return series

The asymmetric leverage effect is clearly seen in news impact curve drawn from EGARCH model fitted to the BSE Bankex, CNX bank and CNX PSU return series. The conditional variance of all returns series indicates larger reaction to past negative shocks as compared to the positive shocks of the equal magnitude.

7. DISCUSSION

Black (1976), Christie (1982), Schewart (1989) and Crouhy & Rockinger (1997) have found that returns are negatively related with the volatility. Studies conducted on volatility in financial markets have completely discarded the volatility as constant and unconditional statistics. Vanilla GARCH model do not allow for asymmetries. So, EGARCH model was employed to study the impact of news on volatility in BSE Bankex, CNX bank and CNX PSU return series. It is found that the returns tend to be less volatile in response to good news and more vulnerable in response to the bad news. Some of the peculiar findings on impact of news are as follows:

1. News affects stock markets.
2. Positive and negative stock return innovations have different impact on the volatility.
3. Volatility following bad news is found to be higher than following good news.

The results of the present study is based on the daily returns indices only and these results can be further improved by extending the methodology on high frequency data to explore the volatility dynamics in Indian banking sector returns.

8. CONCLUSION

EGARCH model proposed by Nelson is employed to determine the asymmetries in the volatility. The daily banking sector return series are statistically studied for stationarity and autoregressive conditional heteroskedasticity. The results confirmed the stationarity and presence of ARCH effect in the return series. There is high persistent volatility in the BSE Bankex, CNX bank and CNX PSU return series. The conditional variance of the BSE Bankex, CNX bank and CNX PSU return series reacts differently to equal size of negative and positive shock. The news impact curve clearly indicates that an unanticipated decrease in return series leads to more uncertainty as compared to an unanticipated increase of equal size. This study will help the investors to estimate and forecast volatility in a better way for developing their risk management strategy.

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