Estimation of Persistence and Predictability of Volatility in The Indian Banking Sector

Dr. Vandana Dangi
Assistant Professor, Government College for Women, Rohtak

Abstract

The impulsiveness in investment's price is volatility and its meticulous estimation and forecasting is valuable to investors in the risk management of their portfolio. Earlier volatility of an asset was assumed to be constant. However, the pioneering studies of Mandelbrot, Engle and Bollerslev on the property of stock market returns did not support this assumption. The family of autoregressive conditional heteroskedasticity models were developed to capture time-varying characteristics of volatility. The present treatise attempts to study the presence of autoregressive conditional heteroskedasticity in four Indian banking sector indices viz. BSE Bankex, BSE PSU, CNX bank and CNX PSU. The daily banking sector indices for the period of January 2004 to December 2013 were taken from the online database maintained by the Bombay Stock Exchange and the National Stock Exchange. The data of four indices was studied for stationarity, serial correlation in the returns and serial correlation in the squares of returns with the help of Augmented Dickey–Fuller test, Box-Jenkins methodology and autoregressive conditional heteroscedasticity models respectively. The results of ACF, PACF and Ljung–Box Q test indicates that there is a tendency of the periods of high and low volatility to cluster in the Indian banking sector. All the four banking sector indices display the presence of ARCH effect indicating the presence of volatility clustering. Engle's ARCH test (i.e Lagrange multiplier test) and Breush-Godfrey-Pagan test and ARCH model confirmed the high persistence and predictability of volatility in the Indian banking sector.

Key Words: Autoregressive conditional heteroskedasticity, Box-Jenkins methodology, stationarity and Volatility clustering

I. Introduction

The Indian banking sector has marvelous industry structure with peculiar features in form of sector consolidation, freedom to deploy capital, regulatory coverage, good corporate governance, labor reforms and human capital development. The several notable efforts made by the banking industry are reflected in favorable metrics like profitability, growth and reducing non-performing assets. Banking industry in India has established an outstanding track record of innovation, growth and value creation even during the global crisis. This is reflected in their market valuation. Dangi (2011) studied the dynamics of competition in Indian banking industry and the results of entropy, exponential index, herfindahl index, Gini coefficient and concentration coefficient confirmed the fair degree of competition and concentration among scheduled commercial banks operating in India. The improved regulations, innovation, growth and value creation in the sector make it a highly competitive sector. This sector has emerged as one of the most attractive investment avenues for masses not only for depositing their money in various deposit schemes but also to invest their money in their securities. Investors sacrifice their present benefits in order to earn future benefits after analyzing the market. Investors have their own assumption regarding the market efficiency and accordingly they employ technical analysis or/and fundamental analysis to evaluate various investment alternatives. Investor has to create and draft his/her own investment plan depending upon their risk tolerance level, expectations and convenience. The evaluation of an investment avenue is not an easy task rather it includes five perspectives, viz. risk, rate of return, marketability, tax shelter and convenience. The most important perspective for the majority of investors is the risk i.e. the volatility or variation in expected rate of return to actual rate of return.

The prediction of volatility in financial market is vital to investors because it indicates a measure of risk exposure in their investment. Investors need to apply statistical methods to evaluate investment alternatives in terms of risk. Traditional volatility estimators are dispersion, variance, standard deviation and squared returns over a period. These traditional estimators assume that volatility is constant and unconditional. Most financial models like CAPM, APT etc. are based on a constant one period forecast variance i.e. constant beta. Mandelbrot (1963) noticed that "large changes in asset prices tend to be followed by large changes-of either sign-and small changes tend to be followed by small changes." He found that volatility tend to move in clusters. The higher volatility periods were followed by higher volatility and lower volatility periods were followed by lower volatility. The traditional estimators were based on 'backward looking concept' whereas forecasting and modeling volatility is a forward-looking concept that requires employment of sophisticated models. The accurate modeling and forecasting of the variance has received a lot of attention in the investment community. Engle (1982) had proposed ARCH process (autoregressive conditional heteroskedasticity 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. The conditional variance was allowed to be a function of prior period's squared errors and its past conditional variances. The introduction of ARCH models by Engle and their generalization by Bollerslev 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 study the volatility clustering. They further captured 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. They further concluded that volatility clustering is not attributable to an auto correlated news-generation process around public information. They found consistency in their results of large-capitalization firms in Japan and the U.K. 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, spill over between the US and Indian markets were present in Sensex and Nifty. She further concluded that the 'weekend effect' was not present in Indian stock market. Connolly, Robert A. and Stivers, Christopher Todd (2005) studied volatility clustering 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 shocks 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 Exchange. 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. 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. Ahmed, Shahid (2007) modelled the volatility of stock returns in Indian market for the period 1997-2006. He employed GARCH family models to explore the persistence and volatility clustering in NSE Nifty and BSE Sensex. He found persistence and volatility clustering in both indexes. Bose Suchismita (2007) examined the characteristics of return volatilities in the NSE Nifty index and its futures market. She found mean reversion and volatility clustering in both series. There was fair degree of volatility persistence in the equity market and its future index market. There was evidence of volatility linkages between the futures and spot markets. Contemporaneous transmission effects were tested across volatilities of NSE Nifty index and its futures market on their daily data by using an asymmetric (threshold) GARCH model. She further concluded that the futures market plays a leading role in as compared to spot market in assimilating information. 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. Surya Bahadur G.C (2008) modelled volatility of the Nepalese stock market using daily return series from July 2003 to Feb 2009. He had applied different classes of estimators and volatility models to understand the pattern of volatility. He found GARCH (1,1) model as the most appropriate for volatility modelling in the Nepalese market. There was no significant asymmetry in the conditional volatility of returns. He finally concluded that there was time-varying volatility in the Nepalese stock market (i.e. volatility clustering) and a high persistence predictability of volatility. Thiripalraju, M. and Acharya Rajesh (2010) modelled the volatility of the various indices of NSE and BSE. They found volatility clustering in the daily returns of indices of NSE and BSE. They estimated different GARCH models for various indices of two premier Indian stock exchanges. They found that GARCH (1, 1) with MA (1) in the mean equation fit better as compared to other models. They further concluded that there was volatility transmission between the two markets. 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 found volatility clustering in NASDAQ, DJIA and HANG SENG stock markets. 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. Hartz, Christoph and Paolella, Marc S. (2011) used GARCH models to capture the volatility clustering inherent in financial returns series. They used volatility measures based on OHLC (open high low close) data.

They found that OHLC measures were superior to be used as naive estimator. 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. The capability of the EGARCH (1, 1) model in forecasting for both periods lending support 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 and Nifty data respectively. Joshi, Prashant Mahesh and Pandya, Kiran (2012) investigated volatility in the stock markets of India and Canada by using various volatility and diagnostic tests on daily closing price data from January 2002 to July 2009. They found conditional heteroscedasticity in both the stock markets. Their findings revealed that the GARCH (1, 1) model successfully capture the time-varying volatility. The persistence of volatility in Indian stock market was marginally less than Canadian stock market. Veredas, David and Luciani, Matteo (2012) introduced an approximate dynamic factor model for forecasting large panels of realized volatilities. They estimated the model by means of principal components with low dimensional maximum likelihood and applied it to a panel of 90 daily realized volatilities pertaining to S&P100 from January 2001 to December 2008. Their model captured the stylized facts of panels of volatilities including co-movements, clustering, dynamic volatility, long memory, skewness and heavy tails. They further proved that their model performed fairly well in forecasting especially in period of turmoil. 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. Jacobsen, Ben and Dannenburg, Dennis (2013) investigated volatility clustering with the help of modelling approach. Their approach was based on the temporal aggregation results for generalized autoregressive conditional heteroscedasticity models. They found that volatility clustering was present in high-frequency financial data and even monthly data exhibit significant serial dependence in the second moments. They further concluded that the estimation of low-frequency models by using temporal aggregation reduced parameter uncertainty substantially. 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 of 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 behaviour differ across provinces. More densely populated provinces as compared to less populated provinces exhibited stronger volatility clustering of house prices. Wang Jun and NiuHongli (2013) investigated the statistical behaviours of long-range volatility in Shanghai composite index and Hang Seng index for a financial price model by applying autocorrelation analysis and GARCH(1,1) model. They found volatility clustering in the indexes. They also employed de-trended fluctuation analysis to evaluate the corresponding long-range memory behaviours.

Studies conducted on volatility in financial markets have completely discarded the volatility as a constant and unconditional statistics. Academicians and researchers have given lot of attention to the volatility dynamics in the developed and emerging financial markets. They confirmed the presence of volatility clustering in the overall returns indices. But there is lack of exploration of dynamics of volatility in the sectoral indices of banking in India. The present treatise is an attempt to fill this lacuna by discovering the presence of clusters in the returns of banking sector. The present study also investigates the clusters in public sector banks indices of two largest stock exchanges of India as Indian banking sector is largely public in nature (Public sector banks hold more than sixty seven per cent of total assets of all scheduled commercial banks).

II. Objectives of Study

1. To study the volatility clustering in terms of autoregressive conditional heteroskedasticity in four Indian banking sector indices viz. BSE BANKEX, BSE PSU, CNX bank and CNX PSU.
2. To explore the persistence and predictability of volatility in Indian banking sector.

III. Research Methodology

Database

The daily stock price data for the period of January 2004 to December 2013on BSE BANKEX, BSE PSU, CNX bank and CNX PSU have been taken from the online database maintained by the Bombay Stock Exchange and the National Stock Exchange.

Econometric Methodology

The data of four indices was studied for stationary, serial correlation in the returns and serial correlation in the squares of returns through following statistical tests:

1. **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:

$$\Delta y_t = \propto + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \qquad (1)$$

The unit root test is carried out under the null hypothesis $\gamma < 0$ against the alternative hypothesis of $\gamma < 0$. 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.

2. **Autocorrelation function (ACF) and Partial Auto correlation Function (PACF):** Tintner(1953) defined autocorrelation as "lag correlation of a given series with itself, lagged by a number of time units". The autocorrelation at lag t by r_t is given by

$$r_t = \frac{\sum_{i=k+1}^{n}(X_i - \bar{X})(X_{i-k} - \bar{X})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \qquad \ldots\ldots\ldots\ldots (2)$$

All autocorrelations at lags 1, 2,….n together make up the autocorrelation function. Partial auto correlation function measure the relationship between X_t and X_{t-k}in time series after removing the effects of othertime lags 1, 2,...,k − 1.The return is white noise in case the ACF and PACF coefficient lie within the critical values i.e. ±1.96(1/N).

3. **Box-Jenkins Methodology:** Box Jenkins methodology is used in the present treatise to model the conditional mean equation. The Ljung–Box Q statistics test the overall randomness on the basis of number of lags. It is also known as portmanteau test that indicates whether any group of autocorrelations of a time series are different from zero. A peculiar point to note here is that this test is not applied to the original series

rather it is applied to the residuals of a fitted ARMA model. The null hypothesis of Ljung–Box test is that the residuals from the ARIMA model have no autocorrelation. This test statistic is defined as:

$$Q = n(n+2)\sum_{k=1}^{h}\frac{p_k^2}{n-k} \tag{3}$$

Where *n* is the sample size,

p_k is the sample autocorrelation at lag *k*,

h is the number of lags being tested.

The critical region for rejection for significance level (α) is $Q > \chi^2_{1-\alpha,h}$ (it is the α-quantile of the chi-squared distribution with *h* degrees of freedom).

4. **Breush-Godfrey-Pagan Test:** It is based on the Lagrange multiplier test principle that is used to test heteroscedasticity 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 heteroscedasticity is examined by regressing the squared residuals on the independent variables:

$$\hat{u}^2 = \Upsilon_0 + \Upsilon_1 x + \tag{4}$$

5. **Engle's Autoregressive Conditional Heteroscedasticity 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 Heteroscedasticity 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:

$$\alpha_0 = \alpha_1 = \cdots = \alpha_m = 0 \tag{5}$$

The alternative hypothesis is:

$$e_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \cdots + \alpha_m e_{t-m}^2 + u_t \tag{6}$$

where u_t is a white noise error process.

IV. Basic Statistics of the Indian Banking Sector Indices

Daily closing prices have been taken for BSE BANKEX, BSE PSU, CNX bank and CNX PSU and converted to daily returns. The present treatise uses the logarithmic difference of closing prices of two successive periods to calculate the rate of return. The logarithmic difference is expressed in percentage terms indicating symmetry between up and down movements. It is a straightforward idea of a percentage change that eases comparability. The series of banking sector indices have been converted into return series by applying the following formula:

$$R_t = (In\ P_t - \ In\ P_{t-1}) * 100 \qquad \text{…………..(7)}$$

where R_t is the return for day t, P_t is closing prices for day t, P_{t-1} is the closing prices of previous trading day (i.e. intervening weekend and stock exchange holidays were omitted) and In is natural log. The basic statistics of BSE BANKEX, BSE PSU, CNX bank and CNX PSU returns are portrayed in the exhibit 1.

Exhibit 1: Basic statistics of BSE BANKEX, BSE PSU, CNX bank and CNX PSU returns

Descriptive Statistics	BSE BANKEX	BSE PSU	CNX bank	CNX PSU
Mean	0.060937	0.016094	0.058527	0.037815
Median	0.111960	0.121067	0.085848	0.114041
Maximum	17.54832	15.19916	17.23940	16.35230
Minimum	-14.48036	-15.56440	-15.13805	-17.19390
Std. Dev.	2.130526	1.725336	2.164392	2.288140
Skewness	-0.060399	-0.611264	-0.123872	-0.231277
Kurtosis	8.459875	12.93267	8.258576	7.580634
Jarque-Bera	3083.141	10353.26	2864.935	2191.154
Probability	0.000000	0.000000	0.000000	0.000000
Observations	2481	2481	2481	2481

The basic statistics of BSE Bankex, BSE PSU, CNX bank and CNX PSU return have similar values and features in terms of average, skewness and peakedness. However, the variability in the CNX bank return is more than the variability in the BSE Bankex return as the standard deviation of CNX bank return is higher for the period covered in the present treatise. BSE PSU returns exhibit lowest variability whereas CNX PSU returns exhibit highest variability as compared to other banking indices. The value of kurtosis statistics is more than three for all four banking indices. It clearly indicates that the data is leptokurtic i.e. more peaked as compared to the normal curve. Banking indices return series have toomany values near the mean and in the tails of their distribution. The value of probability is zero in all series indicating the rejection of null hypothesis of normal distribution by the Jarque-Bera test. These results confirm the renowned fact that dailystock returns are not normal but are leptokurtic and skewed.

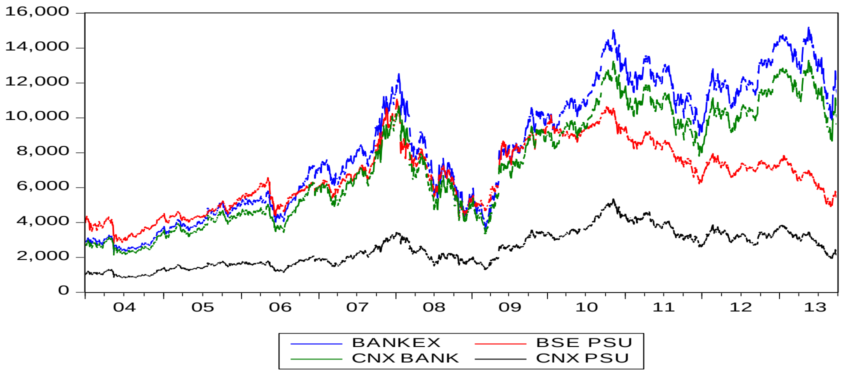


Exhibit 2: Time series of BSE BANKEX, BSE PSU, CNX bank and CNX

The time series of BSE BANKEX, BSE PSU, CNX bank and CNX PSU are first tested for stationarity by graphical method and then by applying Augmented Dickey–Fuller test. The graphical presentation in exhibit 2 for these four indices indicates that time series are non stationary. The augmented Dickey–Fuller test is further applied to test the null hypothesis of unit root. Exhibit 3 indicates the results of augmented Dickey–Fuller test for BSE BANKEX, BSE PSU, CNX bank and CNX PSU.

Exhibit 3: Results of Augmented Dickey–Fuller Test

Panel	Null Hypothesis	t-Statistic	Prob.*
1	BANKEX has a unit root	-1.462900	0.5525
2	BSEPSU has a unit root	-1.927702	0.3197
3	CNXBANK has a unit root	-1.461734	0.5531
4	CNXPSU has a unit root	-1.835731	0.3634

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

The null hypothesis that BSE BANKEX, BSE PSU, CNX bank and CNX PSU series have unit root cannot be rejected as the probability value is greater than 0.05. It means that the series of BSE BANKEX, BSE PSU, CNX bank and CNX PSU are non-stationary time series as confirmed by the results of augmented Dickey–Fuller test. This test conforms that mean, variance and covariance of these series are time variant i.e. they do change over time.

V. Transformation of Non-Stationary Time Series to Stationary Time Series

The non-stationary time series are transformed to stationary time series by estimating differentiated log of closing prices. The return series of BSE BANKEX, BSE PSU, CNX bank and CNX PSU are tested for stationarity by graphical method and then by applying Augmented Dickey–Fuller test. The graphical presentation in exhibit 4 and the results of Augmented Dickey–Fuller test in exhibit 5 indicates that the 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 4: Results of augmented Dickey–Fuller test on transformed series

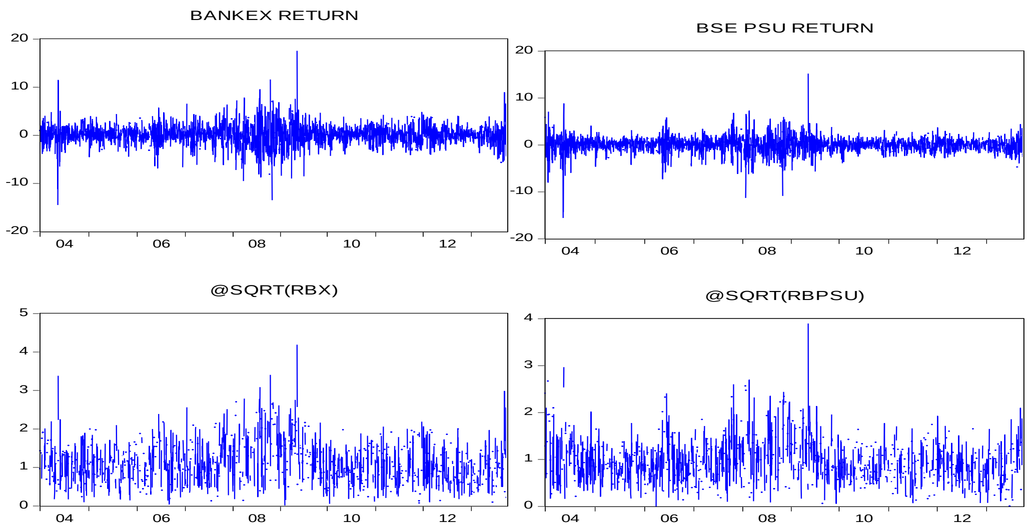
Panel	Null Hypothesis	t-Statistic	Prob.*
1	BANKEX Returns has a unit root	-43.43202	0.0000
2	BSEPSU Returns has a unit root	-44.77882	0.0000

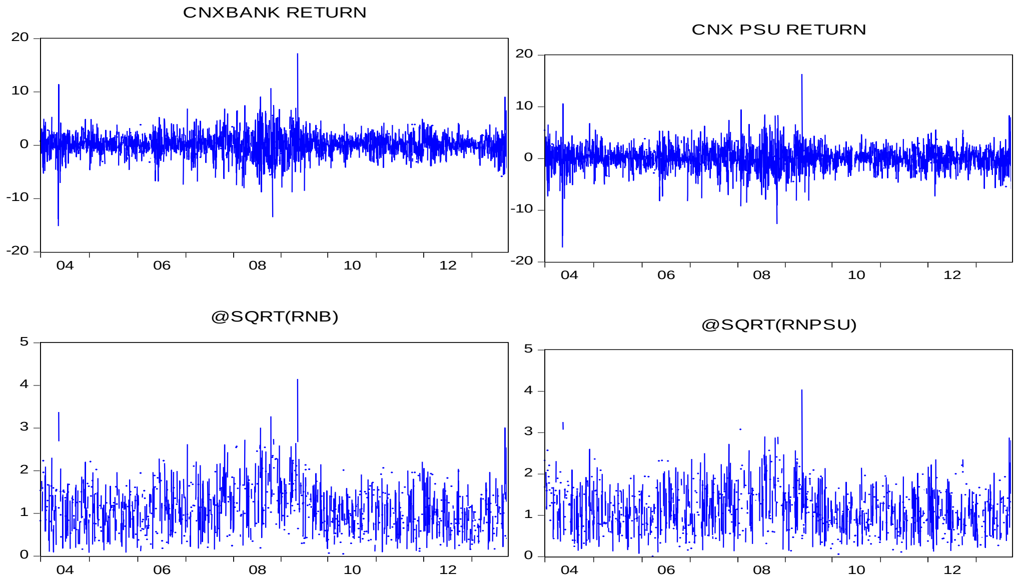
3	CNXBANK Returns has a unit root	-43.42447	0.0000
4	CNXPSU Returns has a unit root	-43.20271	0.0000

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

The visual inspection of the plot of daily returns and squared daily returns on BSE BANKEX, BSE PSU, CNX bank and CNX PSU indicate distinct periods of high volatility and relative stability i.e. volatility clustering. Returns on all four indices continuously fluctuate around a mean value that is close to zero. The movements of returns are in the negative as well as positive territory. Larger fluctuations in the return series have been clustering together and separated by periods of relative calm. The pictorial presentation of return series of all four indices indicates that large returns have been followed by large returns and small returns have been followed by small returns. These patterns lead to contiguous periods of volatility and stability suggesting an apparent volatility clustering.

Exhibit 5: Plot of Daily Returns and Squared Daily Returns





VI. Autocorrelation Analysis

The next stage is to statistically detect the autocorrelation with the help of ACF, PACF and Q statistics in the return series of BSE BANKEX, BSE PSU, CNX bank and CNX PSU. Autocorrelation in the return series is considered as indicative of volatility clustering. The autocorrelation function and partial autocorrelation function are computed. Exhibit 6 portrays the results of ACF, PACF and Q statistics and its associated probabilities values. All four return indices appear to have strong autocorrelations in all lags of these series returns as the probability value is less than 0.05 at each lag. So, null hypothesis of no autocorrelation is not accepted.

The results in exhibit 6 clearly reject the independence assumption for the time series of daily stock returns and confirm the presence of autocorrelation in all lags of these series returns.

Exhibit 6: Results of ACF, PACF and Q Statistics

	Bankex				BSE PSU				CNX Bank				CNX PSU			
Lags	AC	PAC	Q-stat	Prob	AC	PAC	Q-stat	Prob.	AC	PAC	Q-stat	Prob.	AC	PAC	Q-stat	Prob
1	0.136	0.136	45.674	0.000	0.153	0.153	57.885	0.000	0.136	0.136	45.778	0.000	0.142	0.142	49.981	0.000
2	-0.030	-0.050	47.976	0.000	-0.017	-0.042	58.627	0.000	-0.035	-0.054	48.776	0.000	-0.023	-0.044	51.294	0.000
3	-0.008	0.003	48.136	0.000	-0.009	0.000	58.827	0.000	-0.012	-0.000	49.156	0.000	-0.010	-0.000	51.548	0.000
4	-0.026	-0.028	49.876	0.000	0.012	0.013	59.182	0.000	-0.022	-0.023	50.399	0.000	-0.009	-0.008	51.734	0.000
5	-0.055	-0.049	57.484	0.000	-0.045	-0.050	64.127	0.000	-0.059	-0.054	58.987	0.000	-0.058	-0.057	60.021	0.000
6	-0.063	-0.051	67.278	0.000	-0.063	-0.049	73.944	0.000	-0.059	-0.047	67.760	0.000	-0.045	-0.029	65.000	0.000
7	0.000	0.012	67.278	0.000	0.036	0.052	77.136	0.000	0.005	0.015	67.817	0.000	0.005	0.012	65.062	0.000
8	0.039	0.032	71.003	0.000	0.031	0.014	79.529	0.000	0.030	0.022	70.020	0.000	0.016	0.010	65.681	0.000
9	0.032	0.020	73.487	0.000	0.030	0.027	81.768	0.000	0.033	0.025	72.800	0.000	0.047	0.044	71.080	0.000
10	0.029	0.020	75.570	0.000	0.037	0.031	85.113	0.000	0.030	0.020	75.040	0.000	0.033	0.019	73.859	0.000
11	0.019	0.010	76.491	0.000	-0.023	-0.039	86.419	0.000	0.018	0.009	75.815	0.000	0.006	-0.002	73.962	0.000
12	-0.008	-0.011	76.636	0.000	-0.028	-0.018	88.433	0.000	-0.007	-0.009	75.943	0.000	-0.014	-0.014	74.485	0.000
13	-0.008	0.000	76.803	0.000	0.011	0.025	88.754	0.000	-0.009	-0.001	76.141	0.000	-0.019	-0.013	75.358	0.000
14	0.032	0.041	79.402	0.000	0.072	0.069	101.68	0.000	0.032	0.040	78.689	0.000	0.031	0.041	77.698	0.000
15	0.009	0.004	79.593	0.000	0.010	-0.007	101.92	0.000	0.009	0.004	78.889	0.000	0.016	0.011	78.339	0.000

The highly significant Q statistic, as shown in exhibit 6, negates random walk behaviour. In nutshell, all four series of BSE BANKEX, BSE PSU, CNX bank and CNX PSU are non stationary in their level form and stationary in their first difference form. So, these series are further modelled in their returns form. But these return series often display wide swings i.e. varying variance. Ljung–Box Q test is not applied to the original series rather it is applied to the residuals of a fitted ARMA model. Box-Jenkins methodology is applied to detect whether BSE BANKEX, BSE PSU, CNX bank and CNX PSU return series follow a pure AR process or pure MA process or ARMA process.

Exhibit 7 portrays the estimates of these models obtained from usual ordinary least square (OLS) procedure. OLS estimates 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 hetroelasticity and autocorrelation.

Exhibit 7: OLS estimates

PANEL 1

Dependent Variable: RBX

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.060789	0.047440	1.281399	0.2002
AR(1)	-0.191935	0.128936	-1.488612	0.1367
MA(1)	0.335000	0.123782	2.706377	0.0068

Schwarz criterion	4.338597
Durbin-Watson stat	2.000543

PANEL 2

Dependent Variable: RBPSU
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.013419	0.042006	0.319444	0.7494
AR(1)	0.018023	0.107402	0.167813	0.8667
MA(1)	0.140329	0.106331	1.319737	0.1870
MA(14)	0.070447	0.019930	3.534781	0.0004

Schwarz criterion	3.906766
Durbin-Watson stat	2.001371

PANEL 3

Dependent Variable: RNB
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.058475	0.048232	1.212370	0.2255
AR(1)	-0.189965	0.128107	-1.482864	0.1382
MA(1)	0.334049	0.122981	2.716254	0.0066

Schwarz criterion	4.370253
Durbin-Watson stat	2.001321

PANEL 4

Dependent Variable: RNPSU

Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.035338	0.052962	0.667220	0.5047
AR(1)	0.141851	0.019863	7.141355	0.0000

Schwarz criterion	4.477086
Durbin-Watson stat	1.988834

The most common Durbin Watson test to detect autocorrelation is inapplicable in these autoregressive models. So, Engle's ARCH test and Breush-Godfrey-Pagan test and ARCH model are further applied in these ARMA models to test the persistence and predictability of volatility in the Indian banking sector. The residuals of these specified models are tested for ARCH-LM and the results of the same are displayed in exhibit 8 and 9.

Exhibit 8: Results of Breusch-Godfrey Serial Correlation LM Test

PANEL 1			
F-statistic	0.070244	Prob. F(2,2475)	0.9322
Obs*R-squared	0.140746	Prob. Chi-Square(2)	0.9320
PANEL 2			
F-statistic	0.861229	Prob. F(2,24724)	0.4228
Obs*R-squared	1.725357	Prob. Chi-Square(2)	0.4220
PANEL 3			
F-statistic	0.231206	Prob. F(2,2475)	0.7936
Obs*R-squared	0.463238	Prob. Chi-Square(2)	0.7932
PANEL 4			
F-statistic	2.495185	Prob. F(2,2476)	0.0827
Obs*R-squared	4.988377	Prob. Chi-Square(2)	0.0826

Exhibit 9: Results of Engle's ARCH test

PANEL 1

F-statistic	150.4625	Prob. F(1,2477)	0.0000
Obs*R-squared	141.9607	Prob. Chi-Square(1)	0.0000
PANEL 2			
F-statistic	241.9709	Prob. F(1,2477)	0.0000
Obs*R-squared	220.6151	Prob. Chi-Square(1)	0.0000
PANEL 3			
F-statistic	186.5545	Prob. F(1,2477)	0.0000
Obs*R-squared	173.6283	Prob. Chi-Square(1)	0.0000
PANEL 4			
F-statistic	278.0425	Prob. F(1,2477)	0.0000
Obs*R-squared	150.1839	Prob. Chi-Square(1)	0.0000

The results of Breush-Godfrey-Pagan test confirm that the estimated variances of the residuals are dependent on the independent variable as the probability value is more than 0.05. Further, the null hypothesis of no homoscedasticity is not accepted as the probability value is zero i.e. Engle's ARCH test confirms the presence of conditional heteroscedasticity in all the four return series of BSE BANKEX, BSE PSU, CNX bank and CNX PSU. The time sequence plot of residuals and standardised residuals that are obtained from usual ordinary least square (OLS) procedure are displayed in the exhibit 10. The standardised residuals are pure numbers that are calculated by dividing residuals by the standard error of the regression. These standardised residuals can be compared with the standard residuals of other regressions. The disregard for autocorrelation may lead to underestimation of variance.

Exhibit10: Correlogram of Residuals and Squared Residuals

	Correlogram of Residuals		Correlogram of Residuals Squared		Correlogram of Residuals		Correlogram of Residuals Squared		Correlogram of Residuals		Correlogram of Residuals Squared		Correlogram of Residuals		Correlogram of Residuals Squared	
Lags	Q-stat	Prob.	Q-stat	Prob.	Q-stat	Prob.	Q-stat	Prob.	Q-stat	Prob.	Q-stat	Prob.	Q-stat	Prob.	Q-stat	Prob.
1	0.0005		142.18		0.002		215.090		0.001		171.780		0.073		246.500	
2	0.0239		215.73		0.483		355.230		0.072		268.150		4.771	0.029	361.790	0.000
3	0.3121	0.576	229.94	0.000	0.755		429.020		0.570	0.450	284.510	0.000	4.778	0.092	391.440	0.000
4	1.2584	0.533	284.94	0.000	1.465	0.226	457.860	0.000	1.172	0.557	320.300	0.000	4.782	0.188	403.180	0.000
5	6.4338	0.092	314.52	0.000	5.113	0.078	471.430	0.000	6.910	0.075	342.440	0.000	10.952	0.027	411.480	0.000
6	14.395	0.006	341.39	0.000	14.269	0.003	480.840	0.000	13.443	0.009	362.300	0.000	14.463	0.013	421.770	0.000
7	14.413	0.013	377.57	0.000	18.529	0.001	499.000	0.000	13.679	0.018	389.100	0.000	14.821	0.022	431.370	0.000
8	17.309	0.008	404.50	0.000	20.399	0.001	507.000	0.000	15.270	0.018	407.150	0.000	14.953	0.037	441.940	0.000
9	18.808	0.009	489.26	0.000	21.627	0.001	532.440	0.000	16.715	0.019	474.150	0.000	18.468	0.018	471.960	0.000
10	20.283	0.009	546.73	0.000	24.831	0.001	557.820	0.000	18.331	0.019	516.350	0.000	20.194	0.017	495.610	0.000
11	20.971	0.013	584.74	0.000	26.281	0.001	572.800	0.000	18.891	0.026	546.020	0.000	20.221	0.027	506.580	0.000
12	21.082	0.021	610.67	0.000	27.497	0.001	579.170	0.000	18.941	0.041	563.380	0.000	20.418	0.040	509.910	0.000
13	21.399	0.029	631.38	0.000	27.771	0.002	599.370	0.000	19.375	0.055	579.120	0.000	21.296	0.046	520.960	0.000
14	24.228	0.019	651.71	0.000	27.782	0.003	607.210	0.000	22.835	0.029	592.400	0.000	24.267	0.029	524.370	0.000
15	24.238	0.029	688.59	0.000	27.824	0.006	634.130	0.000	0.005	-0.002	625.870	0.000	24.267	0.043	548.070	0.000

The lagged squared disturbance terms are statistically significant as probability value is zero at all lags. It implies that error variances are correlated and ARCH effect is present in all return series indicating the clustering effect in daily returns. So, the statistical analysis of all the four return series of BSE BANKEX, BSE PSU, CNX bank and CNX PSU confirms that large shocks to the error process are chased by large ones and small shocks to the error process are chased by small ones of either sign.

VII. Discussion

Volatility is categorized into historical and implied volatility. The volatility in financial instrument's returns over a specified past time period is known as historical volatility whereas volatility observed from past prices/current prices/future prices of the financial instrument is known as implied volatility. Estimation and forecasting of volatility is valuable to investors in the risk management of their portfolio. Earlier volatility of an asset was assumed to be constant. However, the pioneering studies of Mandelbrot, Engle and Bollerslev on the property of stock market returns did not support this assumption. The family of autoregressive conditional heteroskedasticity models were developed to capture time-varying characteristics of volatility. Volatility clustering is the persistence of the amplitudes of price changes. It emerges when a high return is followed by another high return and low return is followed by another low return. This paper investigates the volatility clustering in the banking sector in India. The volatility in the Indian banking sector exhibits characteristics similar to those found earlier in many of the major developed and emerging stock markets. Arrival of information in clusters, different prior beliefs of participants and time gap to abridge the information shocks to resolve their differences are the sources of volatility clustering in Indian banking sector.

VIII. Conclusion

The present treatise confirms the presence of autoregressive conditional heteroskedasticity in four Indian banking sector indices viz. BSE BANKEX, BSE PSU, CNX bank and CNX PSU. The data of four indices was studied for stationarity, serial correlation in the returns and serial correlation in the squares of returns with the help of Augmented Dickey–Fuller test, Box-Jenkins methodology and autoregressive conditional heteroscedasticity models respectively. The results of ACF, PACF and Ljung–Box Q test indicates that there is a tendency of the periods of high and low volatility to cluster in the

Indian banking sector. Engle's ARCH test (i.e. Lagrange multiplier test) and Breush-Godfrey-Pagan test confirmed the high persistence and predictability of volatility in the Indian banking sector. So, ARCH family models will better capture the changing variance i.e. heteroskedasticity found in the returns. These models encompass the capability to capture such effects after leaving white noise errors. This study will help the investors to estimate and forecast volatility in a better way for developing their risk management strategy.

References

[1] Ahmed, Shahid, “Volatility Clustering in Aggregate Stock Market Returns: Evidence from Indian Stock Market”, Prajnan, 2007-2008, Volume 36, Number 4, pp. 307-323.

[2] Bhaskar Sinha, “Modeling Stock Market Volatility in Emerging Markets: Evidence from India” The ICFAI Institute for Management Teachers (IIMT), 2006, Working Paper Series. Bollerslrv, T... 1986, Generalised autoregressive conditional heteroskedasticity, Journal of Econometrics 31, 307-327.

[3] Bose, Suchismita, “Understanding the Volatility Characteristics and Transmission Effects in the Indian Stock Index and Index Futures Market”, ICRA Bulletin, Money & Finance, September 2007, pp. 138-162.

[4] Connolly, Robert A. and Stivers, Christopher Todd, “Macroeconomic News, Stock Turnover, and Volatility Clustering in Daily Stock Returns”, Journal of Financial Research, June 2005, Volume 28, pp. 235-259.

[5] CrouhyMichel and RockingerMichael, “Volatility Clustering, Asymmetry and Hysteresis in Stock Returns: International Evidence”,Financial Engineering and the Japanese Markets, 1997, Volume 4, Issue 1, pp. 1-3.

[6] Daal Elton, Naka Atsuyuki and Yu Jung-Suk, "Volatility clustering, leverage effects, and jump dynamics in the US and emerging Asian equity markets", Journal of Banking & Finance, Elsevier, 2007, Volume 31(9), pp. 2751-2769.

[7] Dangi, Vandana "Dynamics of Competitiveness in Indian Banking Industry",Anvesha-Journal of IES Management College and Research Centre, July-December 2011, Volume 4, Number 2, pp. 1-10

[8] Engle, R.F., "Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation", Econometrica 50, 1982, pp. 877-1008.

[9] Godfrey, L.G.,"Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables", Econometrica 46, 1978, pp. 1293-1301.

[10] Hartz, Christoph and Paolella, Marc S., "Forecasting Financial Time Series: Normal GARCH with Outliers or Heavy Tailed Distribution Assumptions?",Swiss Finance Institute Research Paper, 2011, pp. 11-45.

[11] Hourvouliades.L.Nikolaos, "Volatility Clustering in the Greek Futures Market: Curse or Blessing?" International Journal of Finance and Economics, 2007, Volume 11, pp 41 – 52.

Jacobsen, Ben and Dannenburg, Dennis, "Volatility Clustering in Monthly Stock Returns", Journal of Empirical Finance, 2003,Volume 10, Number 4, pp. 10-20.

[12] John H.H. Lee, "A Lagrange multiplier test for GARCH models" Economics Letters 37, 1991, pp. 265-271.

[13] Joshi, Prashant Mahesh and Pandya, Kiran, "Volatility in Stock Markets of India and Canada", The IUP Journal of Applied Economics, October 2012, Volume 9, Number 4, pp. 72-79.

[14] Kaur, Harvinder "Time Varying Volatility in theIndian Stock Market",Vikalpa, Volume 29, Number 4, October - December 2004, pp. 25-42.

[15] Li Tao, Muzere and Mark Legge, "Heterogeneity and Volatility Puzzles in International Finance", 2009, Retrieved from http://dx.doi.org/10.2139/ssrn.955738 on 17-10-13.

[16] Lin, Pin-te and Fuerst, Franz, "Volatility Clustering, Risk-Return Relationship and Asymmetric Adjustment in Canadian Housing Markets", 2013,Retrieved from http://dx.doi.org/10.2139/ssrn.2197098 on 15-10-13.

[17] Mahmud, Mahreen and Mirza, Nawazish, "Volatility Dynamics in an Emerging Economy: Case of Karachi Stock Exchange", Ekonomskaistraživanja, 2011, Volume 24, Number 4, pp. 51-64.

[18] Mandelbort, B.B., "The Variation of Certain Speculative Prices", Journal ofBusiness 40, 1963, 393-413.

[19] Poskitt. D.S. and A.R. Tremayne, "Testing the specification of a fitted autoregressive-moving average model", Biometrika 67, 1980, pp. 359-363.

[20] RamlallIndranarain, "Has the US Subprime Crisis Accentuated Volatility Clustering and Leverage Effects in Major International Stock Markets?",International Research Journal of Finance and Economics, 2010, Issue 39, pp. 157-169.

[21] Robert A. Connolly and Christopher T. Stivers, "Evidence on the Economics of Equity Return Volatility Clustering" 1999 retrievedfrom http://www.econometricsociety.org/meetings/wc00/pdf/1575.pdf on 11-10-2013

[22] Sarangi, Sibani Prasad and Patnaik, K. Uma Shankar, "Impact of Futures and Options on the Underlying Market Volatility: An Empirical Study on S&P CNX Nifty Index", 10th Indian Institute of Capital Markets Conference Paper, 2006, Retrievedfrom http://dx.doi.org/10.2139/ssrn.962036 on 14-10-13.

[23] Sinha, Bhaskar, “Determining Historical Volatility in Emerging Markets Using Advanced GARCH Models”, The Journal of Investment Strategies, Summer 2012, Volume 1(3), 67-89.

[24] Surya Bahadur G.C, “Volatility Analysis of Nepalese Stock Market”, Journal of Nepalese Business Studies, December 2008, Volume 5, Number 1, pp. 76-84.

[25] Thiripalraju, Dr. M. and H., Rajesh Acharya, “Modeling Volatility for the Indian Stock Market”, The IUP Journal of Applied Economics, January 2010, Volume 9, Number 1, pp. 79-105.

[26] Tintner, G., “The Definition of Econometrics,” Econometrica, 1953, pp. 31-40.

[27] Veredas, David and Luciani, Matteo, “Estimating and Forecasting Large Panels of Volatilities with Approximate Dynamic Factor Models” (formerly entitled A Model for Vast Panels of Volatilities), European Centre for Advanced Research in Economics and Statistics, 2012, WP 2011/28.

[28] WangJun and NiuHongli, “Volatility clustering and long memory of financial time series and financial price model”, March 2013, Digital Signal Processing, Volume 23, Issue 2, pp. 489–498.

[29] Xue Yi and GencayRamazan, “Trading Frequency and Volatility Clustering”,Journal of Banking & Finance, 2012, Volume 36, Issue 3, pp. 760-773.