Volatility Clustering, Risk-return Relationship and Leverage Effect in Indian Public Sector Banks' Returns

***Dr. Vandana Dangi**

Abstract

The public sector banks in India play dominant role in deposit mobilisation and loan advancement to masses due to their capital potency, technological advancement and financial inclusion ideology. Indian investors consider this sector as a reliable investment alternative. They need to evaluate the sector in terms of risk as well as return.The prediction of impact of 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 volatility clustering, risk-return relationship and leverage effect in daily Indian public banking sector indices of Nifty PSU Bank. The indices for the period of January 2004 to October 2016 are taken from the database (online) maintained by the National Stock Exchange Ltd. The data was studied for stationarity and autoregressive conditional heteroscedasticity with the help of Ng-Perron tests, Augmented Dickey-Fuller test, Engle's ARCH test and Breush-Godfrey-Pagan test respectively. The results confirmed that the return series are stationary and ARCH effect is present in return series. GARCH-M was applied to study the risk-return relationship and EGARCH model was employed to study the leverage effect in Nifty PSU Bank return series. The results confirm the presence of highly persistent volatility and asymmetric leverage effect in public banking sector return series. But there is no evidence of risk-return relationship in the series. These findings may help the investors in understanding the risk exposure of their investment in Indian public sector banks and framing their investment strategy to hedge risk in better way.

Keywords: Asymmetries, Autoregressive conditional heteroskedasticity, EGARCH, GARCH-M, Stationarity and Volatility clustering

*Assistant Professor, Ch. Dheerpal Government College, Shalimar Bagh, Delhi, 110088, E-mail: vandanashoora@yahoo.com

Introduction

The public banking sector in India has emerged as one of the most attractive investment avenues for investors. The prediction of risk-return relationship in financial market is vital for investors as it indicates a measure of risk exposure in their investment. Investors need to analyse the dynamics of volatility in response to the news also. They need to find either the return series have symmetrical or asymmetrical response to different kind of news. So, investors study the impact of news on volatility in banking stocks. The accurate modelling and forecasting of variance has received a lot of attention in investment community. Engle, R. F. (1982) had proposed ARCH process to model time varying conditional variance by using past disturbances. Bollerslev, T. (1986) further had generalized the ARCH process by considering conditional variance as a function of prior period's squared errors and its past conditional variances. These refined approaches to model conditional volatility capture the characteristics of the financial data in a far better way. Crouhy, Michel and Rockinger, Michael (1997) applied AT-GARCH (1,1) model to examine the volatility clustering. They applied hysteresis model (HGARCH) to study the 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. Connolly, Robert A. and Stivers, Christopher Todd (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 concluded that volatility decreases following macroeconomic news announcements. 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 clustering in the daily stock returns at index and firm level from 1985 to 2000. They found strong volatility clustering. Sinha, Bhaskar (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. He 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 index from 1997 to 2005. They found no significant changes in the volatility of the indices however there was change in the structure of volatility of indices to some extent. They also found decline in the persistence of volatility in the indices since the inception of futures trading. Ahmed, Shahid (2007) modelled the volatility of stock returns in Indian market from 1997 to 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. Daal Elton, Naka Atsuyuki and Yu Jung-Suk (2007) proposed a mixed GARCH-Jump model for the specific circumstances in emerging equity markets. Their proposed model encompasses asymmetrical volatility response to both normal innovations and jump shocks. Hourvouliades, L. Nikolaos (2007) examined the existence and nature of volatility clustering in the Athens FTSE20 index futures contract. 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 February 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. He finally concluded that there was time-varying volatility (i.e. volatility clustering) and a high persistence predictability of volatility in the Nepalese stock market. Thiripalraju, M. and Acharya, Rajesh H. (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. 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 'open high low close' data. They found that 'open high low close' 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. 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. 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. Jacobsen, Ben and Dannenburg, Dennis (2013) investigated volatility clustering with the help of modelling approach based on the temporal aggregation results for GARCH 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. Lin, Pin-te and Fuerst, Franz (2013) applied a Lagrange multiplier test for the ARCH 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. Wang, Jun and Niu, Hongli (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. Moussa, Wided Ben (2014) used a multivariate GARCH model to explore the relationship between the stock return and the systemic risk in the banking industry in Thailand, Malaysia, Korea, Indonesia and Philippines. The results indicated the presence of interdependencies in all five countries. There was evidence on the relations between the stock return and the systemic risk before and after the Asian financial crises of 1997. Elyasiani, Kalotychou, Staikouras, and Zhao (2015) investigated the return and volatility interdependencies among the UK, the US, the EU and Japanese banks and insurers. They took the time period from 2003 to 2009. They found strong return and volatility transmissions within as well as across banking and insurance industries indicating the strengthened contagious spillover effects. Adhikary, M. and Saha, S. (2016) modelled the phenomena of volatility clustering and leverage effect in S&P BSE Sensex and S&P CNX Nifty returns series using asymmetric GARCH family of models. They concluded that GJR-GARCH model successfully models for both returns series. Thai and Huynh (2016) empirically examined the risk-return tradeoff and volatility in four market-weighted indexes (Vnindex, Hnxindex, VN30 index and UPCOM index) of four sub-industries (insurance, real estate, diversified finance and banks). They employed ARCH, GARCH, GARCH-M, EGARCH, EGARCH-M, GJRGARCH, GJRGARCH-M to capture the asymmetric effect of volatility. They concluded symmetric and asymmetric models are unable to deal with heteroscedasticity and autocorrelation in the residuals on whole financial industry. However, ARCH(2) and GARCH(1,1) were significant on the Vnindex, HNXindex and VN30 index.

Studies conducted on volatility in financial markets have completely discarded the volatility as a constant and unconditional statistics. They confirmed the presence of volatility clustering in the overall returns indices. But there is lack of exploration of dynamics of volatility in the public banking sector in India. The present treatise is an attempt to fill this lacuna by exploring the clusters, risk-return relationship and leverage effect in the returns of Indian public banking sector.

Objective of the study

The present treatise attempts to investigate the volatility clustering, risk-return relationship and leverage effect in Indian public banking sector indices of Nifty PSU Bank.

Research Methodology

Database

The daily Nifty PSU Bank index data for the period of January 2004 to October 2016 has been taken from the database (online) maintained by the National Stock Exchange Ltd. (NSE). Nifty PSU Bank index comprises of twelve companies listed on the 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, Bank of Baroda, Punjab National Bank, Bank of India, Canara Bank, Union Bank of India, IDBI Bank Ltd., Oriental Bank of Commerce, Allahabad Bank and Syndicate Bank.

Econometric Methodology

The present treatise uses rate of return as the volatility in Nifty PSU Bank indices. The series of Nifty PSU Bank indices have been converted into return series by applying the following formula:

$$R_t = (\text{In } P_t - \text{In } P_{t-1}) \times 100 \qquad (1)$$

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

In is natural log

The data is initially studied for stationarity with the help of modern Ng-

Perron tests (2001) and augmented Dickey-Fuller. The data is further tested for autoregressive conditional heteroscedasticity with the help of **Engle's ARCH test (i.e Lagrange multiplier test) and Breush-Godfrey-Pagan test** because 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 ARCH effect to verify either the assumption of constant variance holds good or it is time varying. **GARCH-in-the-Mean Model** developed by Engle, Lilien and Robins (1987) is applied to study the risk-return relationship. This model allows volatility to enter in the mean equation as an explanatory variable. But, this model enforces a systematic response to positive and negative shocks. So, the Nelson's (1991) Exponential Generalised Autoregressive Conditional Heteroscedasticity (EGARCH) model which allows asymmetries is modelled to capture the leverage effect of volatility. There is no need for artificially imposing the non-negativity constraints for the EGARCH Model parameters. The **EGARCH(1,1)** model is defined as follows:

$$In\ (h^2{}_t) = \alpha_0 + \gamma\,(e_{t-1}/h_{t-1}) + \lambda\,[(|e_{t-1}|\,h_{t-1}) - (2/\pi)^{0.5}] + \beta In\ (h^2{}_{t-1}) \qquad (2)$$

Where (h^2_t) = conditional variance

λ = symmetric (GARCH) effect

β = persistence level in conditional volatility

γ = leverage effect

α_0, γ, λ and β are parameters

The model is symmetric in case the value of γ is 0. If $\gamma < 0$, then good (positive) news generate less volatility as compared to bad (negative) news. If $\gamma > 0$, then good (positive) news are more destabilizing than bad (negative) news.

Properties of Nifty PSU Bank Returns Series: Daily closing prices have been taken for Nifty PSU Bank index. The price series is converted to return series. The basic statistics of Nifty PSU Bank return series are portrayed in the table 1:

Table-1: Basic Statistics of Nifty PSU Bank Returns

Descriptive Statistics	Nifty PSU Bank
Mean	0.000364
Median	0.000815
Maximum	0.163523
Minimum	-0.17194
Std. Dev.	0.02246
Skewness	-0.16102
Kurtosis	7.184411
Jarque-Bera	2331.521
Probability	0.000000

The calculated basic statistics of the return series of Nifty PSU Bank reveals the basic characteristics of the data. The positive average statistics of Nifty PSU Bank returns reveals the increase in indices over the period. However, the negative skewness indicates high probability of earning negative returns. The data is leptokurtic as the kurtosis statistics is more than three. The null hypothesis of normal distribution cannot be accepted as the value of probability of Jarque-Bera test is zero. Initially, the Ng and Perron test has been applied to examine stationary. The table 2 indicates the results of the Ng and Perron test for Nifty PSU Bank returns series.

Table 2: Results of Ng and Perron Test

Null Hypothesis: NIFTYR has a unit root
Exogenous: Constant
Lag length: 17 (Spectral GLS-detrended AR based on SIC, maxlag=28)

		MZa	MZt	MSB	MPT
Ng-Perron test statistics		-2.38429	-1.00185	0.42019	9.75747
Asymptotic critical values*:	1%	-13.8000	-2.58000	0.17400	1.78000
	5%	-8.10000	-1.98000	0.23300	3.17000
	10%	-5.70000	-1.62000	0.27500	4.45000

The results clearly indicate that, for the Nifty PSU Bank returns series, the null hypothesis of non-stationary cannot be rejected by all of the Ng-Perron tests. The augmented Dickey-Fuller test is further applied to support the results of the Ng-Perron tests.

Table 3: Results of Augmented Dickey-Fuller Test

Null Hypothesis	t-Statistic	Prob.*
CNXPSU has a unit root	- 49.68827	0.0001

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

The results of Augmented Dickey-Fuller test in table 3 indicate that the Nifty PSU Bank returns series is stationary. The null hypothesis that the returns series has unit root is rejected as the probability value is 0.0001 i.e. less than 0.05.

Volatility Clustering: Mandelbrot (1963) defined volatility clustering in the context that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes." Exhibit 1 portrays the daily returns on Nifty PSU Bank returns series. It is clear from the visual inspection that volatility in public banking sector indices has changed over time. There are clear periods of high and relative calm volatility that suggests volatility clustering in the indices of Nifty PSU Bank.

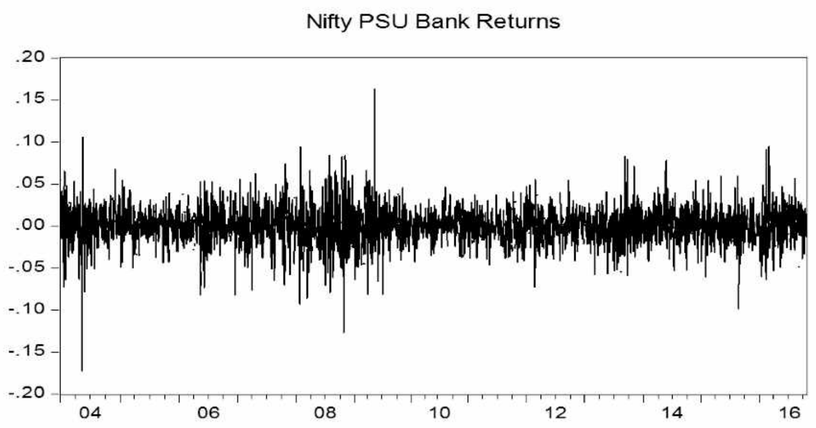

Exhibit 1: Plot of daily returns

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 predictability of volatility in the Indian public banking sector. The results of testing ARCH effect in residuals are displayed in table 4 and 5.

Table 4: Results of Engle's ARCH Test

F-statistic	439.7486	Prob. F(1, 3174)	0.0000
Obs*R-squared	386.4800	Prob. Chi-Square(1)	0.0000

Table 5: Results of Breusch-Godfrey Serial Correlation LM Test

F-statistic	2.323243	Prob. F(2,3172)	0.0981
Obs*R-squared	4.645540	Prob. Chi-Square(2)	0.0980

Engle's ARCH test reveals the presence of conditional heteroscedasticity in the Nifty PSU Bank return series as the probability value is zero. The results of Breush-Godfrey-Pagan test in table 5 also confirm that the estimated variance of the residuals is dependent on the independent variable as the probability value is more than 0.05. The presence of ARCH effect in the Nifty PSU Bank return series clearly indicates the clustering effect in daily returns. So, the statistical analysis confirms that small shocks to the error process are chased by small ones and large shocks are chased by large ones and of either sign.

Risk-Return Relationship: This relationship is studied with the help of GARCH in the mean model. This model has volatility as an explanatory variable in the mean equation. GARCH-M model extends the mean equation in the following form:

$$Y_t = c + \propto g(\sigma_t) + \mu_t \qquad (3)$$

g(.) = arbitrary function of volatility

The estimates from this model are used to examine whether risk is related significantly with return or not. The results of GARCH-M model estimation on Nifty PSU Bank returns series are portrayed in table 6.

Table 6: GARCH-M Model Estimation on Nifty PSU Bank Returns Series

Dependent Variable: NIFTYR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	1.119068	1.703636	0.656870	0.5113
C	0.000198	0.000758	0.260776	0.7943
Variance Equation				
C	1.52E-05	2.21E-06	6.857551	0.0000
RESID(-1)^2	0.082486	0.007074	11.66048	0.0000
GARCH(-1)	0.887656	0.009309	95.35952	0.0000
Durbin-Watson stat	1.746391	Schwarz criterion		-4.876791

The coefficient of variance in the equation is positive (i.e. 1.119068) but statistically insignificant as the p value exceeds the 0.05 and 0.10. It clearly indicates the absence of risk-return relationship.

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 effect. EGARCH model is estimated on the Nifty PSU Bank 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 : EGARCH Model Estimation on Nifty PSU Bank Returns Series

Dependent Variable: NIFTYR
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
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	-0.171019	1.673665	-0.102182	0.9186
C	0.000575	0.000744	0.771956	0.4401
		Variance Equation		
C(3)	-0.495722	0.051552	-9.615938	0.0000
C(4)	0.186015	0.013775	13.50342	0.0000
C(5)	-0.044224	0.007092	-6.235844	0.0000
C(6)	0.954161	0.005772	165.3000	0.0000
Durbin-Watson stat	1.746768	Schwarz criterion		-4.876531

The value of EGARCH parameter in the model estimation of Nifty PSU Bank returns series is close to one. It implies that volatility shocks are persistent in Nifty PSU Bank returns series. The leverage effect term in the equation is C(5)*RESID(-1)/@SQRT(GARCH(-1)). This leverage term is negative as well as significantly different from zero that proves that news impact is assymetric during the sample period. In other words, leverage effect exists for the Nifty PSU Bank returns series during the sample period. The conditional variance of returns series indicates larger reaction to past negative shocks as compared to the positive shocks of the equal magnitude.

Discussion

The results of the present treatise totally affirm the finding of all previous studies in terms of the presence of volatility clustering and asymmetric leverage effect in the returns series. The volatility in the Indian public banking sector exhibits similar characteristics as found earlier in many studies on the emerging and developed stock markets. However, the results are contrary to the results of Lin, Pin-te and Fuerst, Franz (2013) and Moussa, Wided Ben (2014) in terms of the risk-return relationship. These studies found the evidences of risk-return relationships. But the present treatise do not support this relationship as no significant evidence was found for the existence of risk-return relationship in Indian public sector banks' returns series.

Conclusion

The volatility clustering, risk-return relationship and leverage effect in Indian public banking sector indices of Nifty PSU Bank is studied with the help of Engle's ARCH test, Breush-Godfrey-Pagan test, GARCH-M Model and EGARCH model. The results confirm the presence of volatility clustering and asymmetric leverage effect in public banking sector return series. The impact of negative news is more as compared to good news. There is no evidence of risk-return relationship in the public banking sector return series. The findings of present treatise may help the investors in understanding the risk exposure of their investment in Indian public sector banks. These results may also help investors in framing their investment strategy to hedge risk in better way.

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