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Modeling Volatility of Indian Banking Sector

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Abstract:

This article aims at studying the stock price behavior & modeling the volatility of banking sector of India. It also investigates if there is any asymmetric volatility in its return structure. Returns of Bank Nifty index have been used to proxy the Indian banking sector over last ten years period starting from April 1st, 2009- Jan 1st,2019. The return series exhibit heteroskedasticity, volatility clustering & has fat tails. GARCH (1, 1) model has been used to capture the symmetric effects and among the asymmetric models, EARCH (1, 1) has been used. The ARCH in Mean model reported that Indian banking sector stocks offer risk premium to the investors. Long volatility persistence has also been reported over the period considered.

Keywords: Volatility; GARCH; EGARCH; ARCH in Mean

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INTRODUCTION:

Volatility is an important input used is used for investment decisions, construction of portfolio, derivatives valuation risk management, etc. Volatility refers to fluctuations in the stock prices. High volatility is the symbol of inefficient market, but without it high returns cannot be earned. . Higher the volatility, higher the risk. Volatility of returns in financial markets can be a major stumbling block for attracting investment in small developing economies. It has an impact on business investment spending and economic growth through a number of channels. Moderate returns , high liquidity & low level of volatility is taken to be a symptom of a developed market.

The distribution of financial time series shows certain characteristics of Leptokurtosis: i.e. fat tails as compared to normal distribution., Volatility clustering & Heteroskedasticity: i.e. non constant variance.

Economic time series have been found to exhibit periods of unusually large volatility followed by periods of relative tranquility (Engle, 1982). In such circumstances, the assumption of constant variance (homoskedasticity) is inappropriate (Nelson, 1991). One of the most prominent tools for capturing such changing variance was the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) models developed by Engle (1982), and Bollerslev (1986) respectively.

Following the introduction of models of ARCH by Engle (1982) and their generalization by Bollerslev (1986), there have been numerous refinements of the approach to modelling conditional volatility to better capture the stylized characteristics of the data. **The GARCH (1, 1) is often considered by most investigators to be an excellent model for estimating conditional volatility for a wide range of financial data (Bollerslev, Ray and Kenneth, 1992).**

To capture asymmetric effects models such as the Exponential GARCH (EGARCH) of Nelson (1991), the so-called GJR model of Glosten, Jagannathan, and Runkle (1993). Asymmetric effects were discovered by Black (1976) and confirmed by the findings of French, Schwert, and Stambaugh (1987); Schwert (1990); and Nelson (1991), among others. This so called Leverage Effect appears firstly in Black (1976), who noted that:

``a drop in the value of the firm will cause a negative return on its stock, and will usually increase the leverage of the stock which ill cause a rise in the debt-equity ratio which will surely mean a rise in the volatility of the stock".

The characteristics of the Bank Nifty return series are consistent with the above characteristics of financial time series. The aim of this article is to track and model the volatility of banking sector in India. The results of the study will be useful for the market participants in designing & managing their portfolio

Review of literature:

Ajay Pandey(2005), compared Volatility Models and their Performance in Indian Capital Markets using nifty returns. He reported that for estimating volatility, the extreme value estimators perform better on efficiency criteria that the conditional volatility models. In terms of bias, conditional volatility models perform better than the extreme value estimators. Regarding predictive power, extreme value estimators estimated from sample of length equal to forecast period perform better in providing 5 day and one month volatility forecasts than the conditional volatility estimators.

Hakim Ali Kanasro, Chandan Lal Rohra et al. (2009), reported the presence of volatility at the Karachi Stock Exchange by analyzing Indexes namely;'KSE-100 Index' and 'All shares index using GARCH family models The empirical results reported the presence of high volatility at Karachi Stock Exchange during the period analysed.

K.N Badhani (2009) analysed the closing price series of S&P 500 index and S&P CNX Nifty from Jan 1996 to Sept. 2008 to find out the impact of return & volatility in US on Indian stock market . He used AR (1)-TGARCH (1, 1) process to find the leverage effect. He reported the returns in the Indian stock market as more sensitive to negative shocks than US market .

Anil Mittal, Niti Goyal.,(2012) studied the stock price behavior & modeling the volatility of Indian Stock Market using S&P CNX Nifty returns over the ten years period from April 1st, 2000- June 30th, 2010. GARCH (1, 1) & PARCH (1,1) model has been found to be most appropriate model to capture the symmetric & asymmetric effects respectively. The ARCH in Mean model reported that Indian markets do not offer risk premium. They also found persistence in volatility over the period considered.

S.Mohandass ; Renukadevi (2013), modeled the volatility of BSE Sectoral Indices from January , 2001 to June, 2012 using ARMA(1,1) for modeling the average return. They used

GARCH(1,1) model for modeling the volatility of all sector except IT and TECH for which the return series did not exhibit heteroskedastic.

Singh Saurabh; Tripathi L.K (2016), investigated the volatility pattern of Indian stock market using daily closing prices of S&P CNX Nifty Index from 1st April 2001 to 31st March 2016 using both symmetric and asymmetric GARCH class models. GARCH-M (1, 1) and EGARCH (1, 1) estimations are found to be the most appropriate model as per the AIC, SIC and Log Likelihood criterion. The study also reported existence of a positive and insignificant risk premium as per GARCH-M (1, 1) model. The study also found existence of leverage effect in Indian stock market

Singh Amanjot (2017) attempted to capture the conditional variance of Indian banking sector's returns across from year 2005 to 2015 symmetric and asymmetric GARCH class models. He reported the presence leverage effects in the banking sector return volatility and also the persistence in volatility . he found that the global financial crisis had increased conditional volatility in the Indian banking sector during the years 2007 to 2009. He reported (EGARCH) model as the best fit model for capturing time-varying variance in the banking sector.

Kumari Sujata and Sahu Priyanka (2018), estimated empirically the volatility of the Indian stock market by considering twelve indicators of BSE SENSEX. They estimated volatility using various ARCH class models such as ARCH, GARCH, IGARCH, GARCH-M, EGARCH, TARCH, GJR TARCH, SAARCH, PARCH, NARCH, NARCHK, APARCH, and NPARCH from 1st January 2011 to 1st January 2017. They reported ARCH effect in BSEOIL., volatility clustering in BSEREAL as the price of real estate differs according its forms of land and BSEBANK and SPBSEIT both are performing as an important dominant indicators in the market.

Research Methodology

Traditionally volatility modeling techniques were not able to capture heteroskedasticity found in the returns. Non linear models such as ARCH/GARCH are able to capture the peculiar features of the financial time series.

The following GARCH techniques to capture the volatility have been used:

GARCH (1, 1)

The GARCH specification, firstly proposed by Bollerslev (1986), formulates the serial dependence of volatility and incorporates the past observations into the future volatility (Bollerslev et al. (1994)

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

News about volatility from the previous period can be measured as the lag of the squared residual from the mean equation (ARCH term). Also, the estimate of β shows the persistence of volatility to a shock or, alternatively, the impact of old news on volatility.

To find the presence of leverage effect EGARCH (1, 1) has been used. This model was Proposed by Nelson (1991) & is given by the following equation:

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1 ln(\sigma_{t-1}^2 \ \ ) + \beta_1 \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{u_{t-1}}{\sigma_{t-1}}$$

The logarithmic form of the conditional variance implies that the leverage effect is exponential (so the variance is non-negative). The leverage effect is denoted by γ and is present if γ is significantly negative.

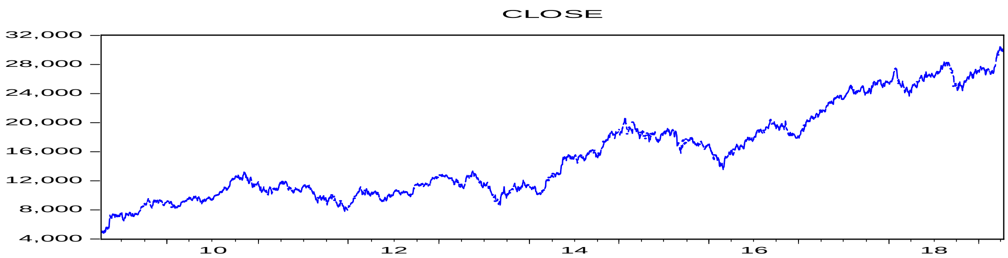
Data & Preliminary Statistics

To model the volatility of the Indian banking sector, we have used daily closing prices of the NSE Nifty as proxy for the Indian banking sector . The data ranges for a period of approximately ten years starting from 1st April 2009 to 1st Jan 2019. The data has been collected from the yahoo finance and has been analysed using Eviews 7 software.

DATA ANALYSIS

T he Graph of the closing price series is shown in fig 1 below. The graph of the series does not show a constant mean and thus reports non stationarity of the data.

Fig.1



To make the series stationary, daily logarithmic returns have been calculated from the closing price series as follows:

$$r_t = \log(p_t - p_{t-1})$$

Where

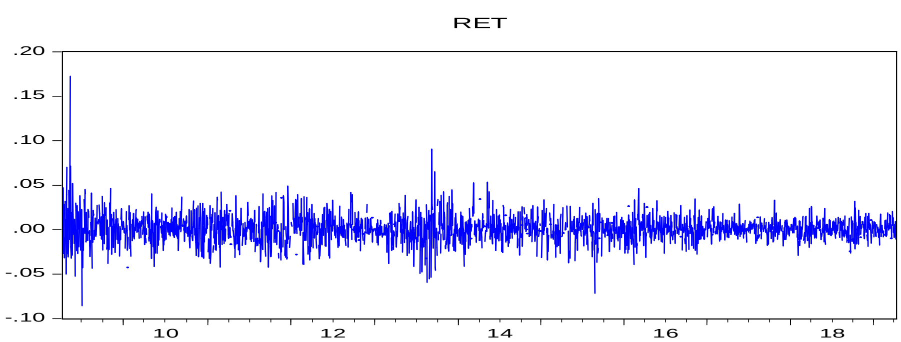
r_t = continuously compounded logarithmic return

p_t =daily closing value of index at day t and

p_{t-1} =closing value of index at day t-1

Thus, the closing value of the index is converted into continuously compounded daily logarithmic return series.

Graph of the return series: Fig 2



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The stationarity of the series can also be confirmed using the Augmented Dickey Test statistic assuming H_o of non stationarity.

Table 1: The result of the ADF Test :

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-43.99100	0.0001
Test critical values:	1% level	-3.432923	
	5% level	-2.862563	
	10% level	-2.567360	

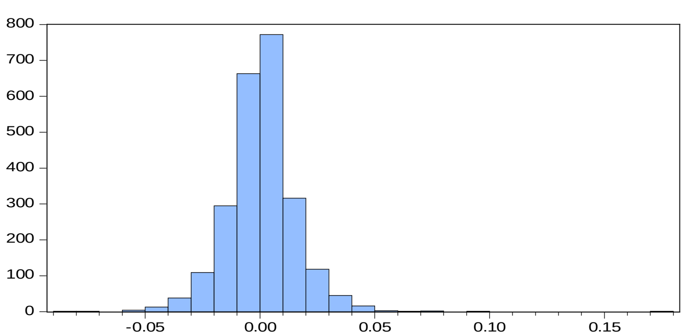
The low p value of the t statistic calls for rejecting the null hypothesis of unit root and accepting the alternate of stationarity.

The graph of the return series is shown in fig 2 above which shows a constant mean which shows stationarity of the data. The series has a non constant variance i.e. heteroskedasticity, which is the typical feature of the time series data. Also volatility clustering in the returns can also be easily seen. If we look at the fig. 2 above, we can easily see that the large changes tend to be followed by large changes and small changes tend to be followed by small changes, which mean that volatility is clustering and the series vary around the constant mean but the variance is changing with time. Thus the return series follow the characteristics of the time series data i.e. heteroskedasticity, leptokurtosis & volatility clustering which means linear model will not be able to capture the volatility of the series therefore non linear models such as ARCH/GARCH need to be used for modelling the volatility of the Indian stock market.

Descriptive Statistics:

Table 2 gives the descriptive statistics of the return series.

Table 2



Series: RET
Sample 4/13/2009 4/10/2019
Observations 2399

Mean	0.000687
Median	0.000763
Maximum	0.172394
Minimum	-0.085440
Std. Dev.	0.015028
Skewness	0.659522
Kurtosis	12.15427
Jarque-Bera	8550.497
Probability	0.000000

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A return of series is around 0.06% with a standard deviation of 1.50 % which indicated large variability in the returns. The skewness of the series is positive which means that there is more probability of earning a positive return and is indicative of the presence of asymmetries in the returns. There is also a lot of variation between the maximum & the minimum return values. The kurtosis of the series is greater than 3, which means that the return series is fat tailed & does not follow a normal distribution which is further confirmed by Jarque Bera Test statistic.

Modelling the Mean

ARMA(2,2) model has been used to model the mean. The residuals of the equation when tested using LJUNG BOX Q Statistic showed no correlation but the squared residuals showed high degree of significant correlation. The residuals when further tested for ARCH effects using ARCH LM Test rejects the null hypothesis of no heteroskedasticity, necessitating the use of non linear models for capturing the volatility.

Table 3. . Heteroskedasticity Test: ARCH

F-statistic	13.02512	Prob. F(5,2386)	0.0000
Obs*R-squared	63.55467	Prob. Chi-Square(5)	0.0000

Modeling the Conditional Variance

Since the ARCH LM test confirms the presence of ARCH effects, we use GARCH (1, 1) model to capture the conditional variance of the series. GARCH (1, 1) is the most popular model amongst all GARCH class models.

The result of the GARCH (1, 1) model is as follows:

Table 4: GARCH (1, 1) Equation

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Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.69E-06	5.69E-07	2.964475	0.0030
RESID(-1)^2	0.054014	0.008487	6.364545	0.0000
GARCH(-1)	0.936672	0.009192	101.9029	0.0000

All the coefficients of the variance equation are highly significant. The sum of σ+ β= 0.98 which shows high persistence in volatility. i.e. a shock in the present will have a lost lasting effect on the future returns .

The residuals of the GARCH(1, 1) model does not show any correlation but the normality test of standardized residuals(as given in table 1 in appendix below) shows that the returns are positively skewed. This skewness could be attributed due to the presence of asymmetric effects in returns . To uncover such dynamics, EGARCH(1,1) has been applied.

ARCH in MEAN

To know if greater risk allows for greater return, GARCH in the mean has been used. The results of the model are as follows:

Table5 : Result for ARCH in Mean

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	3.863221	1.379320	2.800816	0.0051
AR(1)	0.235812	1.307208	0.180394	0.8568
AR(2)	-0.048545	0.250970	-0.193429	0.8466
MA(1)	-0.159384	1.307672	-0.121884	0.9030
MA(2)	0.027557	0.328589	0.083865	0.9332
		Variance Equation		
C	1.92E-06	6.63E-07	2.889513	0.0039
RESID(-1)^2	0.056992	0.009575	5.951982	0.0000
GARCH(-1)	0.933177	0.010315	90.47179	0.0000

The risk term incorporated into the mean equation (as GARCH coefficient) , is highly significant at 5% level which is indicated by the low p value given in table 5 above, which means that increased risk provides for risk premium.

Modeling the Asymmetries

In order to capture the asymmetries in returns of the Indian Banking Sector , EGARCH (1, 1) with variance in mean has been used.

Table 6 : EGARCH (1, 1) with ARCH in Mean

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	3.186633	1.413501	2.254425	0.0242
AR(1)	0.526336	1.490460	0.353136	0.7240
AR(2)	-0.062927	0.248243	-0.253490	0.7999
MA(1)	-0.446139	1.490382	-0.299346	0.7647
MA(2)	0.027573	0.204463	0.134853	0.8927
	Variance Equation			
C(6)	-0.177083	0.034454	-5.139770	0.0000
C(7)	0.096487	0.018124	5.323671	0.0000
C(8)	-0.049405	0.010218	-4.835276	0.0000
C(9)	0.988106	0.003075	321.3858	0.0000

In table 6 above, the coefficients of the variance equation are significant. The asymmetric factor is significantly negative indicating the presence of the leverage effect. Also, the coefficient of variance introduced in the mean equation is significant at 5% level which provides the indication that investment in banking sector provides risk premium to the investor.

Summary:

The returns series in Indian banking sector exhibit volatility clustering , heteroskedasticity & excess peakedness therefore AMA(2,2)- GARCH (1, 1) model has been found to be best for modeling the symmetric volatility. The study also found asymmetric affects in the returns. Bad news increase volatility of the banking sector more than good news. Also, evidence of long persistence in volatility has been seen. The result of the ARCH-in-mean and EGARCH in mean model shows that Indian market do offer any risk premium. i.e. investors taking higher risk are compensated by high returns in the short run

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APPENDIX:

Table 1: Descriptive statistics of GARCH (1, 1) RESIDUALS: