FORECASTING INDIAN BANK STOCK MARKET STATIONARITY AND VOLATILITY ISSUES via GARCH MODELS

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Abstract
Forecasting volatility remains a challenging area of research in the finance. This paper empirically examines how condition of return distribution effects the performance of volatility forecasting using three GARCH models (GARCH, EGARCH and PGARCH). The key focus of this paper is to model stock return volatility by relating different univariate specifications of GARCH type models for daily observations of the S&P CNX 500 index series for the period 1st April 2007 to 31st March 2018. The study found that stock returns have significant ARCH effect. Empirical results specify that the EGARCH model is superior to the GARCH model in forecasting Indian bank stock market's volatility, for all forecast horizons. These findings have important policy implications for financial market participants, investors and policy makers.

Keywords: Volatility persistence, Volatility forecasting, Stationarity, GARCH models
JEL Classification: G21, G34

1.Introduction

Research has found out that a relationship between volatility from one period to the next period exists. The presence of this heteroscedastic relationship may be used for modeling and forecasting future volatility of financial markets. Many time series approaches are applied, including the simple GARCH model, exponential GARCH and the power GARCH model. ARCH models are specially designed to model and forecast conditional variances. Taking into account the serial correlation, the ARCH LM test was used to identify and correct for the existence of ARCH/GARCH in the residuals. Statistical implication of the coefficients of ARCH/GARCH terms, adjusted R-square, Akaike information criterion and Schwarz criterion is used to select the best fitting model.

The Indian banking sector has experienced significant growth in the last decade and has become an important investment target, by providing enormous investment opportunities to investors and portfolio managers. Like in the other sectors in India, investors investing in the banking sector in India face higher risk, as well. Hence, it is essential to study the behavior of the volatility of returns from the Indian banking sector. The focal aim of this paper is to model stock return volatility by relating different univariate specifications of GARCH type models for daily observations of the S&P CNX 500 index series for the period 1st April 2007 to 31st March 2018.

2. Review of Literature

There exist an extensive literature on forecasting stock market volatility, statistical properties of stock market returns, relation between stock market returns and volatilities. Mandelbrot (1963) and Fama (1965) studied the statistical properties of stock returns. French et al., (1987) observed the relationship between stock prices and volatility and reported that unpredicted stock market returns are negatively correlated to the unforeseen changes in volatility. Akgiray (1989) used GARCH (1,1) model to investigate the time series properties of the stock returns and reported that GARCH to be the best of several models in describing and forecasting stock market volatility. Pagan and Schwert (1990) examined that GARCH and EGARCH models enriched with terms proposed by nonparametric approaches yields significant increases in explanatory power. Tse and Tung (1992) reported that EWMA models deliver better volatility forecasts than the GARCH models. Franses and Van Dijk (1996) observed the forecasting ability of the GARCH family of models against random walk model in five European stock markets and found that random walk model performs better, even when the period of 1987 crash was included. On the other hand, many researchers also modeled stock return volatility as negatively correlated with stock returns. (Black, 1976); Cox and Ross, 1976; Bekaert and Wu, 2000; Whitelaw, 2000). Zlato (2008) examined the accuracy of GARCH models in volatility forecasting under various error distributions. Lie et al., (2009) examined how return distribution effects the performance of volatility forecasting using two GARCH models (GARCH-N and GARCHSGED).

In the Indian context, some of the studies that has used ARCH/GARCH model include Karmakar (2005), Kaur (2004), Pandey (2005), Pattanaik and Chatterjee (2000). Karmakar (2005) observed that the GARCH (1, 1) model delivered rationally good forecasts of market volatility. Pattanaik and Chatterjee (2000) employed ARCH and GARCH models for modeling volatility of the Indian financial market. Pandey (2005) explored the extreme value estimators and found that they execute better than the traditional close to close estimators. Kaur (2004) observed the nature and characteristics of stock market volatility in India.

3.Methodology

3.1 Data

The data set used in the study is daily closing index value of Bank Nifty obtained from the official website of National Stock Exchange. The data span over a period of 11 years from April 1, 2007 to March 31, 2018. The number of banks merged in India from 1st April 2007 to 31st March 2018 is 20 across two sectors namely public and private. It includes ten public sector banks and ten private sector banks. Of this, banks with missing data and banks that aren't listed have been removed. This brought down the sample size of listed banks to nine bidder banks and nine target banks.

The return on Bank Nifty is computed as the continuously compounded daily percentage change in the index as shown below:

$$R_t = \ln (I_t / I_{t-1}) * 100 \qquad (1)$$

3.2 Volatility measurement

Volatility refers to the spread of all likely outcomes of an uncertain variable.

$$\hat{\sigma} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t-\mu)^2} \qquad (2)$$

where r_t is the return on day t and μ is the average return over the T-day period. Sometimes, variance, σ^2, is used also as a volatility measure.

3.3 Test of Stationarity – Unit Root Test

A unit root test is a statistical test for the proposition that in an autoregressive statistical model of a time series. It is a test for detecting the presence of stationarity in the series. For randomness purpose, there are two unit root tests. One is Augmented Dickey Fuller (ADF) which is parametric test another most powerful test to check the randomness is the Phillips Perron (PP) unit root test which is non-parametric test.

3.4 ARCH-M

The ARCH-M model is often used in financial applications where the expected return on an asset is related to the expected asset risk which itself is time-variant.

ARCH-M is given by

$$y_t = \alpha_1 + \alpha_2\lambda_t + \alpha_3\sigma_t^2 + \varepsilon_t \qquad (3)$$

3.5 The Generalised Autoregressive Conditional Heteroscedasticity (GARCH) Model

In this model, the conditional variance is represented as a linear function of its own lags. The simplest model specification is the GARCH (1, 1) model

Mean equation $r_t = \mu + \varepsilon_t$ (4)

Variance equation $\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ (5)

where $\omega > 0$ and $\alpha_1 \geq 0$ and $\beta 1 \geq 0$, and.

r_t = return of the asset at time t. μ= average return. ε_t = residual returns, defined as

$\varepsilon_t = \sigma_t Z_t$ (6)

The general specification of GARCH is, GARCH (p, q) is as

$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2$ (7)

where, p is the number of lagged σ^2 terms and q is the number of lagged ε^2 terms.

3.6 The Exponential GARCH (EGARCH) Model

This model captures asymmetric responses of the time-varying variance to shocks and, at the same time, ensures that the variance is always positive.

$L_n(\sigma_t^2) = \omega + \beta_1 L_n(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ (8)

where γ is the asymmetric response parameter or leverage parameter. The sign of γ is expected to be positive in most empirical cases so that a negative shock increases future volatility or uncertainty while a positive shock eases the effect on future uncertainty.

EGARCH (p, q) is as follows:

$L_n(\sigma_t^2) = \omega + \sum_{j=1}^{p} \beta_j L_n(\sigma_{t-j}^2) + \sum_{i=1}^{q} \alpha_i \left\{ \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}}$ (9)

3.7 The Power GARCH (PGARCH) Model

The general asymmetric Power GARCH model specifies σ_t as of the following form:

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-1}^{\delta} + \sum_{i=1}^{p} \alpha_i \left(\left(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-1} \right)^{\partial} \right) \quad (10)$$

where α_i and $\beta_j$are the standard ARCH and GARCH parameters, γ_i are the leverage parameters and δ is the parameter for the power term, and: $\delta > 0$, $|\gamma_i| \leq 1$ for $i = 1,2,\ldots,r$, $\gamma_i = 0$ for all $i < r$ and $r \leq p$. The symmetric model sets $\gamma_i = 0$ for all i.

4.EMPIRICAL RESULTS

4.1 Daily Return Characteristics

Table 1 presents the summary statistics of daily returns of bidder banks, target banks and Bank Nifty. The mean and standard deviation are 0.0011 and 0.0377 for bidder banks; 0.0006 and 0.0461 for target banks; 0.003 and 0.050 for Bank Nifty respectively. The return series of Bank Nifty exhibits a leptokurtic distribution (fat tails) and is negatively skewed. The daily stock returns, are thus, not normally distributed. Further, the significant Jarque-Bera statistics of series indicate a departure from normality through rejecting the hypothesis of symmetric distribution. The return series exhibits the phenomenon of volatility clustering, that is, periods in which the returns show wide swings for an extended time period followed by periods in which there is relative calm.

Table 1: Descriptive Statistics of Daily Returns

of Bidder Banks, Target Banks & Bank Nifty

Statistic	Bidder Banks	Target Banks	Bank Nifty
Mean	0.0011	0.0006	0.003
Median	0.0042	0.0083	0.005
Maximum	0.0998	0.0964	0.294
Minimum	-11.381	-0.11347	-0.174
Standard deviation	-0.0377	-0.0461	-0.050
Skewness	0.2242	0.0716	0.240
Kurtosis	3.9105	6.381	7.988
Jarque-Bera	57.9487 (p=0.0004)	306.589 (0.00103)	1040.11 (p=0.0000)

Source: Estimated Values based on CMIE PROWESS database

4.2 Results of Unit Root Test

Unit root tests are conducted by using ADF and PP tests. The results of unit root test for the return series are presented in Table 2.

<Table 2 Here>

The null and alternative hypotheses of the study are

H_0: There is no stationarity among the successive share prices of banking stocks

Ha: There is stationarity among the successive share prices of banking stocks

The null hypotheses of unit roots for the daily time series data of indices are rejected at their first differences on the ADF with intercept and with trend and intercept. Statistical values in both the cases are less than the critical values at10 per cent, 5 per cent and 1 per cent levels of significance. The null hypotheses that there is no stationarity among the share prices cannot be accepted. The table proved that the null hypothesis of unit roots for all the daily time series indices are rejected at their first differences on the ADF with both intercept, also with intercept and trend. Statistical values in both are less than the critical values at 10 per cent, 5 per cent and 1 per cent levels of significance. Statistical values in both are less than the critical values at 10 per cent, 5 per cent and 1 per cent levels of significance.

Hence it can be concluded that there is stationarity in the share prices. This result is consistent with the findings of **Falojey (2005), Gupta, and Basu (2007), Miclaus, et, al., (2008), Moldovan (2008), and Onour (2009)** and disagree with the results of **Gan, et, al., (2005), Islam and Khaled (2005), Olowe (2002), and Venkatesan (2010)**.

4.3 Testing for Heteroscedasticity

The relevant null hypotheses framed for testing whether a market is efficient are as follows:

H_0: There is no existence of heteroscedasticity in share prices of banking stocks.

Ha: There is existence of heteroscedasticity in share prices of banking stocks.

4.3.1 Empirical Results of Heteroscedasticity Models

GARCH model analysis is carried out for individual shares as well as for share index returns. The test is applied to daily share prices of 18 banks and BANK NIFTY.

GARCH (1,1) Estimation

Tables 3 to 5 show the parameter estimates of different GARCH models for the returns of the index for the specified periods.

Table 3

Results of ARCH LM Test

	Bidder Banks	**Target Banks**	**BKNIFTY**
F-statistic	0.2113	1.7416	3.3189
Obs*R-squared	0.2143	1.6322	3.3174
Prob. F	0.7289	0.5790	0.0686
Prob. Chi-Square	0.7264	0.5772	0.0685

Source: Estimated Values based on CMIE PROWESS database

As it is shown in the table 3, ARCH-LM test delivers strong indication of ARCH effects in the residual series, which shows that we can now progress with the modeling of the index return volatility by using GARCH methodology. The probability of observed R-squared is less than 0.05, so we reject the null hypothesis.

GARCH Model for Volatility - Mean Equation

The results of estimating the GARCH model for volatility – mean equation are reported in Table 4.

<Table 4 Here>

Table 4 present the estimated results of mean equation. The projected coefficient in the mean equation is positive for bidder banks, target banks and Bank Nifty index, which shows that the mean of return sequence significantly depends on past trend. This result shows that as the volatility increases, the returns also correspondingly increase.

GARCH Model for Volatility - Variance Equation

The results of estimating the GARCH model for volatility – mean equation are reported in Table 5.

<Table 5 Here>

In the variance equation from the Table 5, the first three coefficients ω(constant), ARCH term (α) and GARCH term (β) for GARCH (1,1) are highly significant and with expected sign for all periods. The significance of α and β indicates that it has an impact on the conditional variance. In other words, this means that news about volatility from the previous periods has an explanatory power on current volatility. This is also evident from the results that all the estimated coefficients are statistically significant.

The ARCH-LM test statistics for all periods do not exhibit additional ARCH effect. This shows that the variance equations are well identified. Thus the null hypothesis that there is no heteroscedasticity in the residuals is rejected for the sample period. This research is in line with **Akgiray (1989), Engle and Mustafa (1992),** which examined that the banking stock returns exhibit ARCH and GARCH.

The EGARCH (1, 1) model estimated for the returns in the table 5 specifies that all the projected coefficients for all periods are statistically significant at 1 per cent confidence level. The asymmetric (leverage) effect captured by the parameter estimate is also statistically significant with negative sign for all periods; indicate that negative shocks imply a higher next period conditional variance than positive shocks of the same sign, which imply that the existence of leverage effect is observed in returns during the sample period.

From the results of PGARCH (1, 1) in the table 5, the estimated coefficient is significant and positive for the periods, indicating that positive shocks are associated with higher volatility than negative shocks. The volatility persistence (α + β) is considerably high (0.5934 for bidder banks; 0.7554 for target banks; 0.9635 for S&P CNX 500 index and 0.9923 for BANKNIFTY index) and close to unity, thus demonstrating the capability of historical volatility to explain current volatility.

This finding is in line with **Xu (1999), Mittnik and Paolella (2000),Lee et al., (2001), Meric et al., (2007)** which examined time-series features of stock returns and volatility. Thus, there is heteroscedasticity effect of the share prices.

5.Conclusion

This study has attempted to explore the comparative ability of different statistical and econometric volatility forecasting models. A total of three different models were considered in this study. The volatility of the bank index returns have been modeled by using a univariate Generalised Autoregressive Conditional Heteroscedastic (GARCH) models including both symmetric and asymmetric models that captures most common stylized facts about index returns such as volatility clustering and leverage effect, these models are GARCH(1,1), Exponential GARCH(1,1) and Power GARCH(1,1).

The results showed a significant departure from normality and existence of conditional heteroscedasticity in the residuals series. For all periods specified, the empirical analysis was supportive to the symmetric volatility hypothesis, which means returns are volatile and that positive and negative shocks (good and bad news) of the same magnitude will have the same impact on the future volatility level. It is found that negative shocks generate a greater response in volatility than positive shocks of an equal magnitude, which is evident from the speed of information transmission in market. The EGARCH model seems to be an appropriate model for characterizing the dynamic behavior of these returns as it reflects their underlying process in terms of serial correlation, asymmetric volatility clustering and leptokurtic innovation. The results also show that asymmetric GARCH models improve the forecasting performance. Among the models used, the EGARCH model has outperformed GARCH, and PGARCH models.

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Table 2

Results of Unit Root Test

Bank	Statistic	Intercept		Critical Values			Trend and Intercept		Critical Values		
		ADF Test	PP Test	1%	5%	10%	ADF Test	PP Test	1%	5%	10%
Bidder Banks	Level	-8.0095 (0.0000)	-8.2062 (-.0001)	-3.5225	-2.9015	-2.5881	-8.0447 (0.0000)	-9.3077 (-0.0001)	-4.0883	-3.4720	-3.1630
	First Differences	-16.9314 (0.0000)	-44.5089 (-0.0001)	-3.5049	-2.8939	-2.5841	-17.5499 (0.0000)	-44.1384 (-0.0001)	-4.0636	-3.4605	-3.1563
Target Banks	Level	-8.2689 (0.0000)	-8.7005 (-0.0001)	-3.5338	-2.9062	-2.5906	-8.3124 (-0.0001)	-10.3780 (-0.0013)	-4.1041	-3.4794	-3.1673
	First Differences	-15.3704 (0.0000)	-43.2213 (-0.0001)	-3.4897	-2.8874	-2.5807	-15.3043 (0.0000)	-44.6354 (-0.0001)	-4.0421	-3.4504	-3.1506
Bank Nifty	Level	-48.09027 (0.0001)	-47.77023 (0.0001)	-3.43234	-2.86231	-2.56722	-48.08275 (0.0000)	-47.76195 (0.0000)	-3.96111	-3.41131	-3.12749
	First Differences	-83.80175 (0.0001)	-971.5216 (0.0001)	-3.43234	-2.86231	-2.56722	-83.78771 (0.0001)	-981.7511 (0.0001)	-3.96111	-3.41131	-3.12749

Source: Estimated Values based on CMIE PROWESS database

* indicates the significance level at 1%; ‘p-values’ are in parenthesis.

Table 4

Results of GARCH Models for Volatility – Mean Equation

Model		GARCH				E-GARCH				P-GARCH			
Banks/ Index	Parameters	Coefficient	Standard error	Z-statistics	Probability	Coefficient	Standard error	Z-statistics	Probability	Coefficient	Standard error	Z-statistics	Probability
Bidder Banks	Constant	2.43E-04	4.14E-04	2.37E-01	5.72E-01	2.29E-04	3.78E-04	-1.72E-01	6.23E-01	2.91E-04	4.37E-04	3.38E-01	5.65E-01
	AR (1)	0.1155	0.1117	0.8735	0.4505	0.0948	0.1094	0.9826	0.2913	0.1189	0.1176	0.9329	0.4265
Target Banks	Constant	-1.75E-04	2.96E-04	-5.39E-01	5.66E-01	-2.30E-04	3.03E-04	-6.98E-01	5.63E-01	-1.73E-04	3.31E-04	-1.23E+00	5.77E-01
	AR (1)	0.0798	0.0961	0.7800	0.4988	0.0089	0.0909	-0.2775	0.3369	0.0670	0.1028	3.2059	0.5984
BKNIFTY	Constant	0.0014	0.0004	4.0273	0.0001	0.0011	0.0003	3.1233	0.0018	0.0010	0.0004	2.9479	0.0032
	AR (1)	0.1232	0.0181	6.8068	0.0000	0.1259	0.0179	7.0345	0.0000	0.1303	0.0181	7.2029	0.0000

Source: Estimated Values based on CMIE PROWESS database

Table 5
Results of GARCH Model for Volatility - Variance Equation

	GARCH			E-GARCH			P-GARCH		
Parameters	**Bidder Banks**	**Target Banks**	**BKNIFTY**	**Bidder Banks**	**Target Banks**	**BKNIFTY**	**Bidder Banks**	**Target Banks**	**BKNIFTY**
Ω	4.53E-06* (0.0000)	1.55E-06* (0.0000)	8.47E-06* (0.0000)	-5.7656* (0.0000)	-8.2398* (0.0000)	-0.3935* (0.0000)	0.0016* (0.0000)	-0.0001* (0.0000)	0.0002* (0.0000)
Α	0.1805* (0.0000)	0.1384* (0.0000)	0.0984* (0.0000)	0.3673* (0.0000)	0.1561* (0.0000)	0.2064* (0.0000)	0.1473* (0.0000)	0.1795* (0.0000)	0.1084* (0.0000)
ϒ				0.0826* (0.0000)	0.1956* (0.0000)	-0.0542* (0.0000)	-0.1783* (0.0000)	0.0851* (0.0000)	0.2506* (0.0000)
Β	0.4999* (0.0000)	0.6496* (0.0000)	0.8837* (0.0000)	0.3909* (0.0000)	0.1955* (0.0000)	0.9705* (0.0000)	0.4461* (0.0000)	0.5759* (0.0000)	0.8838* (0.0000)
β_1							2.0648* (0.0000)	1.9589* (0.0000)	1.3206* (0.0000)
α + β	0.6804	0.7880	0.9821	0.7582	0.3516	1.1769	0.5934	0.7554	0.9923
AIC	9.0778	8.3893	5.1285	9.0611	8.7068	5.1366	9.0585	8.5261	5.1367
SBC	8.9617	8.2732	5.1185	8.9218	8.5674	5.1246	8.8959	8.3635	5.1227

Source: Estimated Values based on CMIE PROWESS database
* indicates the significance level at 1%; 'p-values' are in parenthesis.