World Applied Sciences Journal 9 (10): 1089-1094, 2010
ISSN 1818-4952

Modeling Volatility of Short Term Interest Rates by ARCH Family Models: Evidence from Pakistan and India

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Abstract: This paper uses the ARCH family models to investigate the volatility of short term interest rates of the Karachi Inter Bank Offering Rate (KIBOR) and Mumbai Inter Bank Offering Rate (MIBOR) in Pakistan and India respectively. We have used the daily data from Pakistan (three month bid rates of the KIBOR) and India (three month rates of the MIBOR). To search out best inter bank offering rate, various time series models are examined which are: GARCH, EGARCH, TGARCH and PARCH. A comparison is also made within sample forecasting performance on the basis of two criteria Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) using all ARCH family models, this comparison suggested that MIBOR interest rate better forecast as compared to KIBOR as it has minimum errors. These findings are powerfully suggested to economists, monetary policy makers and specially the econometricians that the most unpredictability series is KIBOR from Pakistan because the doubt in prices.

Key words: Kibor · Mibor · Garch and Volatility

INTRODUCTION

Pakistan and India faced many social and economic hurdles for establishing stable and better economic prosperity. Among the economic factors interest rate fluctuates and caused unavoidable disturbances at each level of policy making. Therefore it is an important issue and task for the economists and specially the econometricians to formulate the mechanism of functioning the interest rate. The present study is an ample effort.

The estimated population growth rate of Pakistan and India in 2007 is 1.828% and 1.521% respectively, which is very high rate as compared to the other European countries like Australia (0.824%), Norway (0.363%), New Zealand (0.95%), United Kingdom (0.275%), Canada (0.869%), Germany (-0.033%), United state of America (0.894%) and France (0.588%). Another comparison of Pakistan's and India's population growth rate with some other under developing countries is shown in Figure 1. The heavy population of Pakistan and India caused poverty, low per capita income, low business, high inflation rate and made it difficult to work at high interest rate.

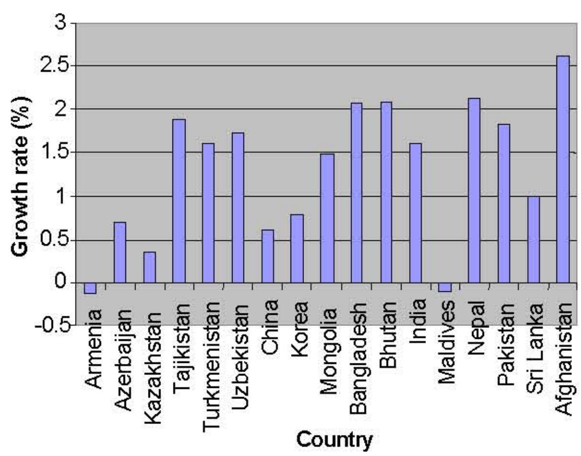

Fig. 1: Population growth rates of under developing countries

There is a large literature on modeling and forecasting volatility, however, few have tested ARCH family models using the literature focusing on the Karachi inter bank offering rate (KIBOR) and Mumbai Inter Bank Offering Rate (MIBOR). A brief review of findings of some of earlier research work is presented as under:

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Engle and Bollerslev [1] proposed correspondingly the Auto-Regressive Conditional Heteroscedasticity (ARCH) and the Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) models could be successfully used when the conditional variance varies over time and when the conditional standard deviation is present rather than variance then PARCH model will be helpful which is proposed by Ding *et al.* [2] with the power ARCH process.

Additionally, Threshold GARCH model was developed by Glosten, Jaganathan and Runkle [3], which is used to capture the leverage effect and Exponential Generalized Auto- Regressive Conditional heteroscedasticity (EGARCH) model was introduced by Nelson [4] who is also used to capture the leverage effect.

Venkatesh [5] compared different models of short term interest rate using one month LIBOR data for three periods June 1973 to December 1989, January 1990 to July 2006 and from June 1973 to July 2006 using ARCH family models, in particular Tse and Yip [6] focused on the differentials between the U.S and Hong Kong Inter bank Offering rates (HIBOR).

Irfan *et al.* [7] developed a model of time varying volatility and asymmetry of KIBOR, daily observations for the period of one month, six month and one year bid rates of the Karachi Inter Bank Offering rates (KIBOR) have used. The empirical period begins in January 2006 and ends in May 2008 making total observations of 693 excluding public holidays. In there study model has made to the most prominent features of the time series of KIBOR such as volatility clustering, excess kurtosis and fattailedness by applying the most popular techniques. GARCH (1, 1) is found to be best to capture the persistence in volatility while EGARCH (1, 1) successfully overcome the so called "leverage effect" in all tenors of KIBOR under study. The selected model GARCH (1, 1) is used for forecasting purpose for all tenors. The study compared one month, six month and one year tenors for best forecasting period on the basis of two criteria Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). This comparison suggested that six month tenor better forecast as compared to other two tenors as it has minimum errors.

In this paper, we detain financial time series characteristics using GARCH, EGARCH, TGARCH and PARCH models. Several studies investigate the performance of ARCH family models on explaining volatility [8-10].

This paper is organized as follows. The next section presents the data used. Section 3 describes the methodology and Section 4 shows the empirical discussion. Finally, we compared the forecasting performance to check the best inter bank offering rate under study.

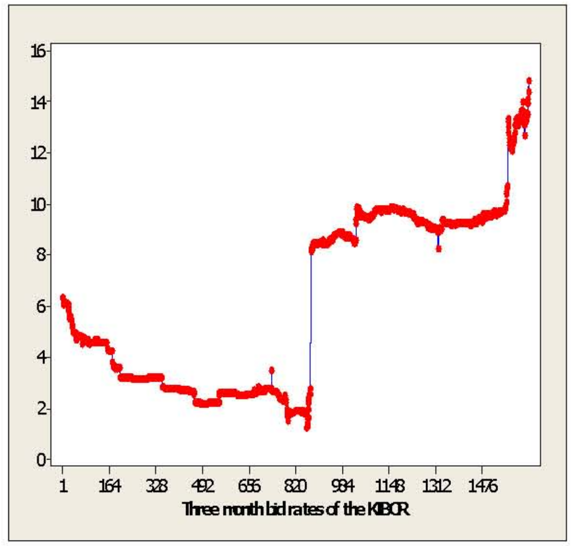

Fig. 2: Plot of three month KIBOR bid rates

Data: The data utilized in this study contains 1639 daily observations on the Karachi Inter Bank Offering Rate (KIBOR) covering the period 2001 to 2008 and 2318 daily observations on the Mumbai Inter Bank Offering Rate (MIBOR) covering the period 2001 to 2008 after eliminates the weekends and holidays in both offering rates. Both KIBOR and MIBOR interest rates are calculated by taking first difference of logs of two consecutive months [8, 10, 11]. Empirical study is performed by using EViews 5.1 and Minitab 15.0 programs.

Properties of the Data: Various descriptive statistics of the daily observations for three month inter bank offering rates of both KIBOR and MIBOR are reported in Table 1. Both interest rates have negative skewness implying that the distributions have a long left tail, which means that the both KIBOR and MIBOR have non symmetric returns. The values of kurtosis are high (greater than three) in both cases which means that the distributions are peaked relative to normal. The return series of KIBOR and MIBOR are non normal according to the Jarque and Bera test [12], which rejects the normality at the 5% level for both distributions. The standard deviations are also high which indicates high level of fluctuations present (i,e. volatility clustering) in both returns. The results are in line with the findings of Chan *et al.* [13] and Floros [10]. Moreover, Figure 2 and Figure 4 present the pattern of the returns series, which clearly exhibits non stationary and

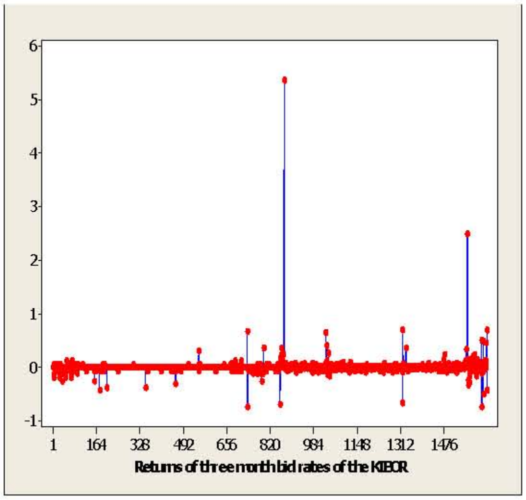

Fig. 3: The return series of KIBOR bid rates

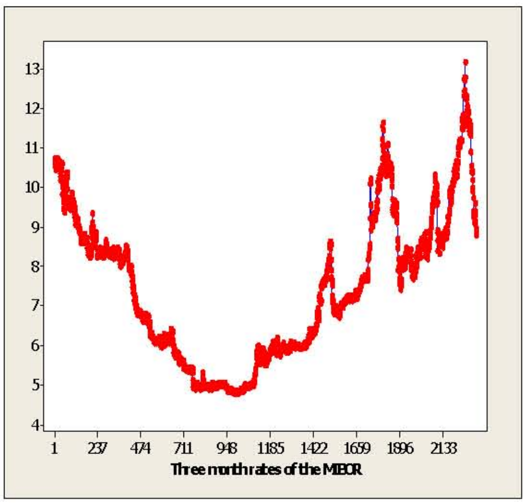

Fig. 4: Plot of three month rates of MIBOR

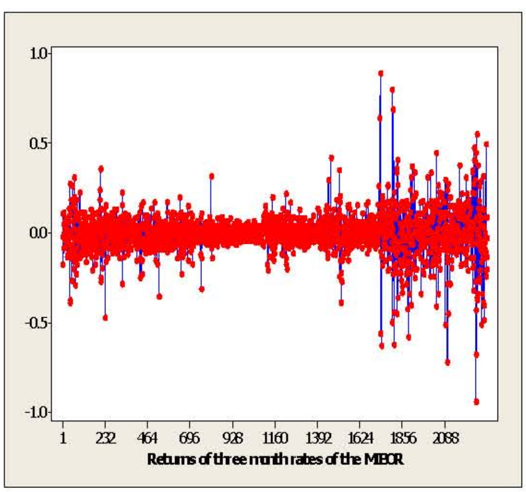

Fig. 5: The return series of the MIBOR

a continuous trend. Furthermore, the ADF test statistic for both returns are less than the critical value, therefore reject the null hypothesis that returns have a unit root. Therefore, daily returns series are stationary. In Figure 3 and Figure 5 return series for both inter bank offering rates show that the mean of the series are now about constant which indicate clearly stationary, even though the variance becomes unusually high which clearly exhibit volatility clustering, which allow us to carry on further to apply the ARCH family models.

METHODOLOGY

In this section, four various ARCH family time series models: GARCH, EGARCH, TGARCH and PARCH will be described briefly.

Bollerslev [14] proposed a GARCH (p, q) which allows for both autoregressive and moving average components in the heteroscedasticity variance. Following literature [9, 10, 7], a simple GARCH model is defined as

$$h_t = \alpha_o + \alpha_1 \varepsilon_{t-i}^2 + \beta_1 h_{t-1} \tag{1}$$

The GARCH (1, 1) will be stationary if $\alpha_1 + \beta_1 < 1$ where α_1 and β_1 must satisfy the non negativity condition.

Exponential Generalized Auto-Regressive Conditional Heteroscedasticity (EGARCH) model was introduced by Nelson [4] who is used to capture the leverage effect noted in Floros [10], Leon [15] and Irfan *et al.* [7]. A commonly used model is the EGARCH (1, 1) given by

$$\ln h_t^2 = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \phi \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_1 \ln h_{t-1}^2 \tag{2}$$

Where ϕ captures the leverage effect.

Furthermore, The Threshold GARCH model was developed by Glosten, Jaganathan and Runkle [3], which is also used to capture the leverage effect. A simple variance specification of TGARCH could be given as

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1} + \phi d_{t-1}^2 \varepsilon_{t-1} + \beta_1 \ln h_{t-1}^2 \tag{3}$$

Where d_{t-1} is a dummy variable that is equal to one if $\varepsilon_{t-1} < 0$ & is equal to zero if $\varepsilon_{t-1} > 0$ and ϕ captures the leverage effect (i.e. asymmetric effect).

TGARCH and the EGARCH models are used to capture the leverage effect but the main difference between these two in EGARCH model, there is no need of nonnegative restriction of the parameters but in TGARCH model parameters must follow the positive condition.

Finally, all ARCH family models discussed in our research paper only deal with the conditional variance. However, a GARCH model using the standard deviation instead of variance was introduced by Taylor [16] and Schwert [17]. Power GARCH model is a generalization of standard deviation GARCH model, which is introduced by Ding *et al.* [2] with the power ARCH process. The PARCH specification is given by

$$h_t^{\beta} = \alpha_0 + \alpha_1(|\varepsilon_{t-1}| - \phi\varepsilon_{t-1})^{\beta} + \beta_1 \ln h_{t-1}^{\beta} \tag{4}$$

Where ϕ detain the asymmetric effect and $\beta > 0$ is the power parameter.

EMPIRICAL RESULTS

As shown by descriptive statistics in Table 1, the distribution of return series does not follow normal distribution which means volatility clustering is present in both returns. First, we model the conditional mean process by AR (p) and MA (q); orders are determined by the Akaike information criterion (AIC) and Schwarz information criterion (SIC). For both indices, we choose ARMA (1, 1) appear to be fitted the best model according to the different criterion and test statistics like Akaike criterion, Schwarz criterion and Durbin- Watson statistics (not reported here). The correlogram of ARMA residuals suggest that the estimated residuals are purely random. Hence, there is no need to look out for another ARMA model for both indices under study. While the squared residuals from ARMA correlogram (not reported) show high quantity of autocorrelation in residuals which allow us to carry on further applying the ARCH family models on both indices.

The results in Table 2 indicate the parameters estimates of ARCH family models. The sum of the ARCH and GARCH coefficients (α_1 + β_1) in the GARCH model exceed to one in KIBOR returns, indicating that volatility shock are very high and the variances are not stationary under GARCH model. However, In MIBOR returns the sum of the ARCH and GARCH coefficients are very close to one in GARCH model, indicating that volatility shock are moderately present.

Furthermore, the asymmetric models EGARCH (1, 1) and TGARCH (1, 1) are used to test the leverage effect. EGARCH (1, 1) model shows positive and significant parameters for both returns (See in Table 2), indicating the continuation of leverage effect and bad news increases volatility term. However, the TGARCH (1, 1) model indicates negative and insignificant parameter in the case of MIBOR returns. PARCH (1, 1) model also confirms that the asymmetric effects are present in both returns.

Table 1: Descriptive Statistics & ADF Tests

A. Inter bank offering rates	Three month bid rates of the KIBOR	Three month rates of the MIBOR
Mean	6.192617	7.456286
Median	4.813000	7.285000
Maximum	14.82000	13.20000
Minimum	1.250000	4.790000
Std. Dev.	3.456001	1.865569
Skewness	0.223769	0.383188
Kurtosis	1.585236	2.258839
Jarque-Bera	150.3678	109.7818
Probability	0.000000	0.000000
Observations	1639	2318
ADF (Level)	0.498988	-1.723160
ADF (1st difference)	-39.24052	-22.95174
B. Returns	**Three month bid Rates of the KIBOR**	**Three month rates of the MIBOR**
Mean	-0.001799	-4.75E-06
Median	0.000000	-0.000411
Maximum	97.57497	10.25159
Minimum	-106.5184	-10.46466
Std. Dev.	4.610246	1.955861
Skewness	-1.623029	-0.029823
Kurtosis	315.0670	6.310348
Jarque-Bera	6643244	1057.829
Probability	0.000000	0.000000
Observations	1638	2317
ADF (Level)	-15.50004	-25.12029
ADF (1st difference)	-19.09954	-20.20698

Notes: Skewness measures the asymmetry of the distribution and Kurtosis measures the tallness or flatness of the distribution. Jarque-Bera is a test statistic to check the whether the series is normal or not. We use ADF test on the level and logarithms of inter bank offering rates of both KIBOR and MIBOR series. ADF test critical values are: (1%) –3.4341, (5%) –2.8631, (10%) –2.5676.

Table 2: ARCH family Models for volatility

Index / Model	α_0	α_1	β_1	ϕ	β
	Part A. Kibor Returns				
GARCH	0.2172 (0.015)	1.5853 (0.209)	0.0623 (0.019)		
TGARCH	0.1828 (0.010)*	0.6176 (0.054)*	0.2395 (0.022)*	0.3599 (0.133)*	
EGARCH	0.1368 (0.023)	0.0225 (0.001)	0.3248 (0.039)	0.0310 (0.061)*	
PARCH	0.2301 (0.053)	1.1008 (0.237)*	0.1152 (0.044)*	-0.0213 (0.054)*	2.5090 (0.515)
	Part B. Miibor Returns				
GARCH	0.1689 (0.027)	0.2894 (0.031)	0.6668 (0.025)		
TGARCH	0.1676 (0.027)*	0.2956 (0.045)*	0.6685 (0.025)*	-0.0154 (0.067)	
EGARCH	-0.2821 (0.024)	0.4393 (0.035)	0.9184 (0.012)	0.0069 (0.031)*	
PARCH	0.1381 (0.024)	0.2733 (0.027)*	0.7053 (0.027)*	-0.0061(0.067)*	1.4944 (0.256)

Notes: Standard errors are in parentheses

* Indicates significant at 5%level

Table 3: Forecasts statistics for KIBOR & MIBOR Rates

Index	Model	Rmse	Mae
Kibor	GARCH	4.144	1.113
	TGARCH	4.116	1.113
	EGARCH	4.192	1.112
	PARCH	4.104	1.112
Mibor	GARCH	1.613	0.878
	TGARCH	1.614	0.873
	EGARCH	1.612	0.885
	PARCH	1.613	0.869

Notes: RMSE measures of forecasting performance i, e.

$$\text{RMSE} = \sqrt{\frac{\sum_{t=T+1}^{T+k}(\hat{y}_t - y_t)^2}{h}}, \text{MAE} = \frac{\sum_{t=T+1}^{T+k}|\hat{y}_t - y_t|}{h}$$

Finally, forecasting performance of both returns are compared through Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The results of forecast performance are reported in Table 3 for both returns under study. This comparison suggested that MIBOR better forecast as compared to KIBOR as it has minimum errors. A similar observation was made in the study of Magnus and Fosu [18].

CONCLUSION

Pakistan and India faced many social and economic hurdles for establishing stable and better economic prosperity. The heavy population of Pakistan and India caused poverty, unemployment, low per capita income, low business, high inflation rate and made it difficult to work at high interest rate. Our objective of this work is to search out the best time series models among Generalized Auto Regressive Conditional Heteroscedasticity (GARCH), Threshold Generalized Auto Regressive Conditional Heteroscedasticity (TGARCH), Exponential Generalized Auto regressive Conditional Heteroscedasticity process (EGARCH) and Power Auto Regressive Conditional Heteroscedasticity (PARCH) to give best prediction of both returns. We investigated the volatility and asymmetric affect for both KIBOR and MIBOR returns. The results from all ARCH family models demonstrate that high volatility is present in KIBOR returns however, volatility shock are moderately present in MIBOR returns. TGARCH is the best models in both returns as they have all the parameters are significant. PARCH (1, 1) model is selected the second best model using the criteria of Student's t distribution. All ARCH family models are compared using the within sample forecasting performance on the basis of two criteria RMSE and MAE, this comparison suggested that MIBOR better forecast as compared to KIBOR as it has minimum errors. These findings are powerfully suggested to economists, monetary policy makers and specially the econometricians that the most unpredictability series is KIBOR from Pakistan because the doubt in prices.

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