Forecasting short term interest rates
using ARMA, ARMA-GARCH and ARMA-EGARCH models

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Abstract

Forecasting interest rates is of great concern for financial researchers, economists and players in the fixed income markets. The purpose of this study is to develop an appropriate model for forecasting the short-term interest rates i.e., commercial paper rate, implicit yield on 91 day treasury bill, overnight MIBOR rate and call money rate. The short-term interest rates are forecasted using univariate models - Random Walk, ARIMA, ARMA-GARCH and ARMA-EGARCH and the appropriate model for forecasting is determined considering six-year period from 1999.The results show that interest rates time series have volatility clustering effect and hence GARCH based models are more appropriate to forecast than the other models. It is found that for commercial paper rate ARIMA-EGARCH model is most appropriate model, while for implicit yield 91 day Treasury bill, overnight MIBOR rate and call money rate - ARIMA-GARCH model is the most appropriate model for forecasting.

Keywords: Interest rates, forecasting, ARIMA, GARCH

Introduction

Forecasting interest rates is gaining more attention in the recent years, particularly because interest rate is a key financial variable that affects decisions of consumers, businesses, financial institutions, professional investors and policymakers. Movements in interest rates have important implications for the economy's business cycle and are crucial to understanding financial development and changes in economic policy. Timely forecasts of interest rates can therefore provide valuable information to financial market participants and policymakers. Forecasts of interest rates can also help to reduce interest rate risk faced by individuals and firms. Forecasting interest rates is very useful to central banks in assessing the overall impact (including feedback and expectation effects) of its policy changes and taking appropriate corrective action, if necessary. An important constituent of the package of structural reforms initiated in India in the early 1990s was the progressive deregulation of interest rates across the broad spectrum of financial markets. As part of this process, the Reserve Bank has taken a number of initiatives in developing financial markets, particularly in the context of ensuring efficient transmission of monetary policy. An important consideration in this regard is the signaling role of monetary policy and its implications for equilibrium interest rates.

In India, interest rate prediction was not given much focus until the beginning of 1990s. This is due to the administered interest rate mechanism that India has been following. But since the beginning of economic reforms and the liberalization of capital market, the interest rates were allowed to float, except the benchmark Bank Rate and the interest rate on savings deposits. Since then, the question of determining the interest rates has become a big issue.

One of the most visible tasks of economists is to forecast interest rates, yet with relatively little success in public opinion. Indeed, interest rates prove to be extremely difficult to predict, while often, large amounts are at stake. However, there is now an amazing and confusing spectrum of the methods to be used for forecasting. Hence this paper attempts to identify the best models to forecast short-term interest rates using random walk model, ARIMA model, ARMA-GARCH and ARMA-EGARCH model.

The rest of this paper is organized as follows: Section II gives the literature survey, which describes the applications of ARIMA and GARCH models. Section III describes the data, sample and methodology used. Section IV gives the empirical results of the study. Finally, the findings are summarized in Section V.

Section II: Literature Survey

ARIMA models have been used for forecasting different types of time series and have been compared with a benchmark model for its validity. Leseps and Morell (1977) in their study found that the exchange rate follows a long-term trend with short-term fluctuation. Therefore, to capture the long term trend, many authors had used Auto regressive Integrated Moving Average (ARIMA) model as proposed by Box-Jenkins (1976), to forecast the exchange rate. Pagan and Schwert (1990) found evidence that ARIMA models performed well when compared to nonparametric and Markov switching models.

Chen (1995) introduced a new pre-differencing transformation for the AR1MA model for forecasting S&P 500 index volatility. The out of sample forecasting performance of the ARIMA model using the new pre-differencing transformation was compared with the out of sample forecasting performance of the mean reversion model and the GARCH model. The ARIMA model using the new pre-differencing transformation introduced in this study was found to be superior to both the mean reversion model and the GARCH model in forecasting monthly S&P 500 index volatility for the forecast comparison periods used in this study.

Dharmaratne (1995) specifies, estimates, and validates an ARIMA model for forecasting long-stay visitors in Barbados. The accuracy of the short-term forecasts surpasses most recent forecasting studies. The implication of the study is that customized model building may be highly rewarding in terms of accurate forecasts compared to standard or simple methods. Abdel- Aal and Al-Garni (1997) used univariate Box-Jenkins time-series analysis for modeling and forecasting monthly domestic electric energy consumption in the Eastern Province of Saudi Arabia. They found that, compared to regression and abductive network machine-learning models previously developed on the same data, ARIMA models require less data, have fewer coefficients, and are more accurate.

Bianchi, *et. al* (1998) analyze the use of additive and multiplicative versions of Holt–Winters (HW) exponentially weighted moving average models and compare it to Box–Jenkins (ARIMA) modeling with intervention analysis and find that ARIMA models with intervention analysis perform better for the time series studied. Ho and Xie (1998) investigate the approach to repairable system reliability forecasting based on the Autoregressive Integrated Moving Average (ARIMA) models. It is theoretically and statistically sound in its foundation and no a priori postulation of models is required when analysing failure data. Comparison is also made with the traditional Duane model. It is concluded that ARIMA model is a viable alternative that gives satisfactory results in terms of its predictive performance.

Chaveza, *et. al* (1999) used Univariate Box-Jenkins time-series analyses (ARIMA models), for modeling and forecasting future energy production and consumption in Asturias. The optimum forecasting model obtained for each energetic series had a satisfactory degree of statistical validity (low approximation errors) and are suitable for use as reference inputs in a regional energetic plan for the period 1997–98. Madura, *et. al* (1999) assess the forecast bias and accuracy of the three commonly used forecast methods for 12 divergent emerging market currencies. The random walk method outperformed the forward rate and ARIMA methods for some emerging market currencies, and was not outperformed by these alternative methods. In general, it appears that the incorporation of expectation components by the implicit forward and ARIMA methods do not improve the forecast, and actually reduce forecast accuracy in some cases.

Slini, *et. al* (2001) used stochastic autoregressive integrated moving average ARIMA model for maximum ozone concentration forecasts in Athens, Greece. For this purpose, the Box-Jenkins approach is applied for the analysis of a 9-year air quality observation record. The model developed is checked against real data for 1 year. The results show a good index of agreement, accompanied by a weakness in forecasting alarms. Saab, *et. al* (2001) investigate different univariate-modeling methodologies and try, at least, a one-step ahead forecast for monthly electric energy consumption in Lebanon. Three univariate models are used, namely, the autoregressive, the autoregressive integrated moving average (ARIMA) and a novel configuration combining an AR(1) with a high pass filter. The AR(1)/high pass filter model yields the best forecast for this peculiar energy data. Lim and McAleer (2002) used various Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) models over the period 1975(1)–1989(4) for tourist arrivals to Australia from Hong Kong, Malaysia and Singapore. The fitted ARIMA model is found to be valid when tourists arrivals were forecasted for Singapore for the period 1990(1)–1996(4)..

In the Indian context, Mahadevan (2002) found that while forecasting 10 year government securities yield, ARIMA has a marginally better directional accuracy than that of the moving average model in a static forecast, whereas the lagged moving averages for 10-year government securities outperforms ARIMA model in dynamic forecasting.

Financial time series have volatility clustering effect and hence ARCH based models are being used to develop a more parsimonious model to forecast financial time series. The literature shows that attempt has been made to forecast the returns or the volatility of returns using ARCH based models. Kearns and Pagan (1991) examined monthly volatility of the Australian stock market over the period 1875-1987, and fitted ARCH, GARCH and EGARCH models to the data. It was found that the asymmetric EGARCH (1, 2) model out performed the other models for forecasting the volatility of the returns.

Rabemananjara and Zakoian(1993) show that, it is possible to relax the positivity constraints on the parameters of the conditional variance, using TGARCH. The authors have applied it to the French stock returns and concluded that unconstrained models provide a greater generality of the paths allowing for non-linearities in the volatility. Nicholls and Tonuri(1995) use several asymmetric GARCH processes to explain and model volatility of Australian stock return data. They have used daily returns on the Australian Fifty Leaders Statex-Actuaries Accumulation Index from 4 January, 1988 to 31 December 1991, i.e., a series of 1023 observations. They have used excess returns, that is, the returns series converted to an excess return series by subtracting the daily yield on 90-Day Bank Bills. They find that stock return data is typically negatively skewed and attempt to incorporate such asymmetry in the model using EGARCH, AGARCH and GJR GARCH. They conclude that the asymmetric EGARCH(1,1) model provides a suitable description of the variance data.

Brooks and Lee (1997) use ARCH/GARCH models to investigate Australian financial futures data. The extent to which the parameters of the models change over time, are examined by analysing the data, contract by contract. The results vary over time and simple models such as the ARCH (1) model provides a reasonably good fit to the data. Tabak and Guerra (2002) examine the relationship between stock returns and volatility over the period of June 1990 to April 2002. The relationship between stock returns and volatility is tested using seemingly unrelated regressions methods and AR(1)-E-GARCH(1,1) estimation. The returns are proxied by BOVESPA Index. They conclude that using both a SUR methodology and an AR(1)-EGARCH(1,1) estimation changes in volatility are negatively related to stock returns.

Friedmann and Sanddorf-Köhle (2002) analyze volatility dynamics in the Chinese stock markets and compared it with the EGARCH with the GJR GARCH model. The empirical results, which were quite stable under the alternative specifications, reflect the different dynamics due to the market segmentation in domestic A-shares and foreign B-shares. For the daily returns on A-shares they find that there is highly significant impact of the number of non trading days on volatility, as well as a significant reduction of volatility by introducing the price change limit. The evidence is more mixed for the B-shares. For the analysis of the impact of news on volatility, they propose a modification of the news impact curve. Using the concept of a conditional news impact curve, they show that in periods of high volatility there is a potential acceleration of the news impact in the GJR GARCH model, while the news impact remains invariant under the EGARCH approach.

Yu(2002) evaluates the performance of nine alternative models such as the random walk, historical average, Moving average, Simple regression, exponential smoothening, Exponentially weighted moving average, ARCH, GARCH and Stochastic volatility models for predicting stock price volatility using daily New Zealand data using four different measures - root mean square error, mean absolute error, Thiel coefficient and Linex to evaluate the forecasting accuracy. He concludes that the (i) stochastic volatility model provides the best performance among models; (ii) ARCH-type models can perform well or badly depending on the form chosen; (iii) the performance of the GARCH(3,2) model, the best model within the ARCH family, is sensitive to the choice of assessment measures; and (iv) the regression and exponentially weighted moving average models do not perform well according to any assessment measure, in contrast to the results found in various markets. Gazda and Vyrost (2003) attempt to forecast the volatility of the Slovak share index using GARCH, TGARCH and EGARCH models for the time period 1 August 1997 to 27 September 2002 taking the first 1000 observations for quantification and statistical verification of the model and the last 173 for the demonstration of a forecast expost. They conclude that the best results were achieved with the EGARCH model. In the period under consideration the existence of an asymmetric effect was confirmed.

Inference

The literature review shows that ARIMA modeling is widely used in various time series for forecasting, such as exchange rates, government securities, tourist arrivals, air quality observation, energy production and consumption and S&P 500 index volatility and it is a powerful tool for short-range forecasting. However, GARCH and EGARCH models are extensively used in forecasting volatility of stock returns and there is very little attempt to apply it to other financial time series. The literature also shows that the financial time series have the volatility clustering effect, which is best captured by GARCH models. In order to capture the asymmetric effect, the EGARCH model is used to forecast volatility and the literature shows that EGARCH model outperforms the traditional models. Thus, an attempt is made to forecast returns of short-term interest rates using GARCH and EGARCH taking into account the AR and MA terms and the results are compared with ARIMA and random walk models.

Section III: Data and Methodology

Data

In order to forecast the returns, log returns i.e., ln (Y_t)-ln (Y_{t-1}) is used for forecasting the short term interest rates. Daily data of Overnight MIBOR and Weighted average call money, fortnight data of commercial paper rate from Jan 1999 to June 2004 and weekly data of Implicit yield of 91 day Treasury bill from Jan 1993 to June 2004 are used. The total data points for Call money rate, commercial paper rate, Implicit yield on 91 day Treasury bill and overnight MIBOR are 2007, 1571, 339 and 134 respectively. Out of which 1604, 1256, 271 and 108 points are used as in-sample data and 403, 315,68,26 points are used as out of sample data for call money rate, commercial paper rate, Implicit yield on 91 day Treasury bill and overnight MIBOR respectively.

Methodology

The four interest rates have been forecasted using the random walk model, ARIMA model, ARMA-GARCH and ARMA-EGARCH model. The goodness of fit of the model is tested using correlogram of residuals, LB statistic or Q-test, Serial correlation Breusch Godfrey test.
The stationarity has been tested using ADF test with and without drift and trend, the AR(p) is determined using PACF and MA(q) is determined using ACF. The no. of lagged terms to be included in the model is identified based on the minimum value of AIC and SBC critieria.The ARIMA model is tested for ARCH effects using the ARCH LM test and the measures of performance are calculated for the static and dynamic forecasts made for the out-sample period. The in-sample data constituting 80% is used for estimating the coefficients of the parameters and the out-of- sample data-20% is forecasted. The forecasted results from Random walk model, ARMA, ARMA-GARCH, ARMA-EGARCH models using static and dynamic forecasting are compared based on the predictive power using the three forecasting accuracy measures: Root Mean Square Error, Mean Absolute Error and Thiel Inequality Coefficient: Theil’s U statistic can be rescaled and decomposed into 3 proportions of inequality – bias, variance and covariance – such that bias + variance + covariance = 1 and these measures were also calculated.

Section IV: Results

4.1 DESCRIPTIVE STATISTICS AND STATIONARITY TESTS FOR RETURNS

The descriptive statistics shown in Table 1 indicates that on an average all the interest rate returns is 0.49 for all interest rates except overnight MIBOR which has an average return of 0.70. The four series are tested for stationarity using the Augmented Dickey Fuller test and it is found that all the four returns series are stationary in level as shown in Table 2 as the ADF statistic (absolute value) is greater than the critical value for all interest rates.

4.2 FORECASTING SHORT-TERM INTEREST RATES USING RANDOM WALK MODEL

The four interest rates are forecasted based on its past value alone using the Random Walk model. The estimated parameters are shown in Table 3. The coefficients of Y_{t-1} terms of commercial paper returns, overnight MIBOR returns and Call money returns are significant at 1% level of significance. The developed models are tested for serial correlation using Breusch-Godfrey Serial correlation test. It is found that except for Implicit yield on 91 day Treasury bill, the other models suffer from serial correlation as shown in Table 4. On examining the correlogram of Residuals, except for the residuals of Implicit yield on 91 day Treasury bill, the residuals of other interest rates have significant lags indicating that it is not a good fit. Hence, the random walk model is good fit for Implicit yield on 91 day Treasury bill but it is not a good fit for the other interest rates - Commercial paper rate, Overnight MIBOR rate and call money rate.

4.3 FORECASTING INTEREST RATES USING ARMA MODEL

Since Random Walk model did not yield the best model for forecasting short-term interest rates ARIMA model is being explored.

Identifying the Lag Length

The appropriate AR and MA terms are identified for each of the interest rate returns using the correlograms of Autocorrelation function (ACF) and Partial autocorrelation function (PACF), which indicates the significant lags for the MA and AR terms. Based on the correlograms and the minimum AIC and SBC criteria, the models estimated are shown in Table 5. It is found that commercial paper rate depends only on its past 3 values. Implicit yield on 91 day Treasury Bill depends on the previous two weeks returns, while Overnight MIBOR and weighted average call money show that it is dependent on 6-day lag and 5 day lag respectively. This may be because daily data is used for these two short-term interest rates. The lag of the MA terms for Implicit yield on 91 day Treasury Bills, commercial paper rate, Overnight MIBOR and weighted average call money based on the correlogram are 1, 0, 5 and 6. All the AR and MA terms are significant at .01 level of significance.

Validity of the Model

The developed ARMA model is checked for serial correlation using Breusch-Godfrey Serial Correlation LM Test with the null hypothesis that serial correlation is present. The Breusch-Godfrey Serial correlation LM test results are shown in Table 6, which indicate that the developed models do not suffer from serial correlation for all the interest rates and both the indices. The correlograms of the residuals obtained from the above developed ARIMA models for the short-term interest rates indicate that they are white noise except for overnight MIBOR and weighted average call money rate. Hence, the model developed is a good fit.

Testing for ARCH effects

The residuals of the ARIMA models developed are tested for ARCH effects using the ARCH LM test and the result shows that the ARIMA models developed for Commercial paper rate, Implicit yield on 91 day Treasury bill, Overnight MIBOR rate and Call money rate suffer from ARCH effects as indicated in the Table 7. Since variance of the errors is not a constant, heteroscedasticity exists for the residuals of the four short-term interest rates. Thus, though the serial correlation test, correlogram of residuals show that ARIMA model is a good fit for Commercial paper return and implicit yield on 91 day Treasury bill, the ARCH effects are present and hence the model is not a good fit. In the case of Overnight MIBOR and call money rate, though serial correlation is rejected, correlogram and ARCH LM test show that the model is not a good fit. Hence, it is necessary to develop a better model to capture the ARCH effects in the four interest rate series.

4.4 FORECASTING USING GARCH MODEL

The GARCH model is developed for the four interest rates. The residuals of the ARIMA models are in non-linear form, that is, they have the volatility clustering effect and this is indicated by the significant coefficients of the ARCH(1) and GARCH(1) terms in the variance equation of Implicit yield of 91 day Treasury bill, overnight MIBOR and call money rate as indicated in Table 8.

The non-negativity constraint is also satisfied i.e., the coefficients of the ARCH (1) and GARCH(1) are positive for all the terms in the variance equation. The sum of the coefficients on the lagged squared error and lagged conditional variance is less than one in all the cases. This sum is close to unity in the case of overnight MIBOR and call money indicating that shocks to the conditional variance will be highly persistent. A large sum of these coefficients will imply that a large positive or a large negative return will lead future forecasts of the variance to be high for a protracted period. The variance intercept term ' c' is very small as expected. The residual series obtained from the above estimated model is tested for ARCH effects to see if ARCH effects are captured well in the estimated model. Table 9 indicates that the ARCH effects are not present in the model estimated after taking into account the GARCH terms. Thus, the GARCH model is better than the ARIMA model for forecasting interest rates. However, the GARCH models estimated do not take into account the leverage effect and hence the EGARCH models are developed to test whether asymmetric effect is present.

4.5 FORECASTING USING EGARCH MODEL

The variance equation of the EGARCH models developed for the interest rates are given in Table 10. The results show that asymmetric effect is present in call money rate and commercial paper rate and it is statistically significant. The negative coefficient estimates of RES/SQR [GARCH](1) in call money rate and commercial paper rate suggest that negative shocks have a higher next period conditional variance than positive shocks of the same sign. In the case of overnight MIBOR, the sum of the coefficients of |RES|/SQR[GARCH](1), RES/SQR[GARCH](1) and EGARCH(1) are greater than unity indicating that the conditional variance will tend to infinity as the forecast horizon increases and hence this model cannot be used for forecasting overnight MIBOR. Since the EGARCH coefficients of the Implicit yield on 91 day Treasury bill and weighted average call money rate are not significant, EGARCH model is not appropriate for forecasting these two interest rates. The residual series obtained from the above estimated model is tested for ARCH effects to see if ARCH effects are captured well in the estimated model. Table 11 indicates that the ARCH effects are not present in the model estimated after taking into account the EGARCH terms.

4.5 COMPARISON OF MEASURES OF PERFORMANCE FOR THE SHORT-TERM INTEREST RATES FORECASTS USING ARMA , ARMA-GARCH, ARMA-EGARCH AND RANDOM WALK MODEL

The out of sample static and dynamic forecast of interest rate returns using ARMA, ARMA-GARCH, ARMA-EGARCH and Random walk models is done taking 80:20 ratio.

a) Commercial Paper rate

As the residuals of the Random walk model suffer from the serial correlation and residuals of the ARMA model suffer from ARCH effects, these models are not appropriate for forecasting CP rate. Though the root mean square error (see Table 12) shows that the GARCH static is better, the coefficients were not significant. Hence, it could be concluded that the asymmetric effect is present in Commercial paper returns and is best captured by AR (3)-EGARCH (1, 1) using Static forecast.

b) ***Implicit yield on 91-day Treasury bill***

Based on the measures of performance (see Table 13) RMSE and MAE, the ARMA (1,1)-EGARCH(1,1) model is better. However, the coefficients of this model were not significant. Though the residuals of the random walk model were not serially correlated and the correlograms showed that it is a white noise, none of the measures of performance is low for this model. Hence, ARMA(1,1)-GARCH(1,1) outperforms the Random walk, ARMA(1,1) and ARMA(1,1)-EGARCH(1,1) which is also indicated by the variance proportion and covariance proportion measures and thus the ARMA (1, 1)-GARCH (1,1) using static forecast is better than the other models developed.

c) Overnight MIBOR

The measures of performance - Mean Absolute Error, Bias proportion and Covariance proportion indicate that the Random walk model is better but the residuals of the model suffer from serial correlation (see Table 14). The root mean square error indicates that the ARMA using static forecasting is better but the residuals of this model suffer from ARCH effects. Though the Variance proportion is low for ARMA (6,5)-EGARCH, the sum of the coefficients of the variance equation is greater than unity. Hence, it is concluded that ARMA (6,5)-GARCH(1,1) using dynamic forecasting is the best model for forecasting overnight MIBOR returns.

d) Weighted average Call Money rate

Based on the measures of performance, the results are mixed (see Table 15). The residuals of Random walk and ARMA model suffers from serial correlation and ARCH effects respectively. Though variance proportion and covariance proportion are low for EGARCH model the coefficients were highly significant for the ARMA-GARCH model indicating high volatility persistence. Hence it is concluded, that ARMA (5,6)-GARCH(1,1) using dynamic forecasting is the best model for forecasting call money rate returns

Section V CONCLUSION

The short-term interest rates are forecasted using ARMA, ARIMA-GARCH, ARIMA-EGARCH and Random Walk models. The results indicate that the short-term interest rates do have volatility clustering effect in the time series and this captured by the GARCH/EGARCH models developed. Moreover, the ARIMA and random walk model developed were not a good fit. The comparison of the models for forecasting Short-term interest rates - Implicit Yield on 91 day Treasury bill, call money and overnight MIBOR show that ARIMA-GARCH is an appropriate model for forecasting. However, to forecast commercial paper returns, ARIMA-EGARCH model is more appropriate. Hence, investors, bankers, corporates and regulators can use the ARIMA-GARCH model to forecast the implicit yield on 91 day Treasury bill, call money and overnight MIBOR and ARIMA-EGARCH model for CP rate forecasting as the error terms in interest rates have volatility clustering behavior which is best captured by GARCH/ARCH terms. The major contribution of this paper is that short term interest rates have volatility clustering effect and hence GARCH/EGARCH based models are more appropriate for forecasting than random walk or ARIMA models. However, there is scope for further validating the model by testing the model for different time periods.

Table 1 Descriptive Statistics of Short-Term Interest Rate Returns (1999-2004)

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
Mean	0.494086	0.498930	0.704803	0.499774
Median	0.497655	0.500000	0.70000	0.500000
Maximum	0.628381	0.826100	2.252408	1.159803
Minimum	0.323924	0.255800	0.069996	-0.217658
Std. Dev.	0.058625	0.035882	0.109913	0.072915
Skewness	-0.247364	0.519568	5.328598	-0.518282
Kurtosis	3.459242	20.81379	74.09550	31.11589
Jarque-Bera	2.525112	8623.631	283819.3	66129.71
Probability	0.282930	0.000000	0.000000	0.000000

Table 2: Stationarity Test Augmented Dickey Fuller Test - Short term interest rates

Variables	ADF Test Statistic	1% Critical Value*
Commercial Paper returns	-6.290660	-4.0320
Implicit Yield of 91 day Treasury bills returns	-9.141223	-2.5718
Overnight MIBOR returns	-23.36767	-3.9692
Weighted Average Call money returns	-24.88257	-3.9680

Table 3: Random Walk Model – Short term interest rate returns

$$\mathbf{Y_t = c + Y_{t-1}}$$

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
Y_{t-1}	-0.374313 (-4.503527)*	-0.086662 (-1.592090)	-0.243647 (-9.972191)*	-0.061095 (-2.749990)*
c	-0.010253	-0.002445	-0.000539	-0.000416

Table 4: Breusch-Godfrey Serial Correlation LM Test –Residuals of Random Walk Model

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
F-statistics	13.34655	1.086234*	10.93613	8.896853
* Indicates Null Hypothesis of serial correlation is rejected				

Table 5: ARMA models for the Short-term Interest Rates

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
AR coefficients	AR(1):-0.527378 AR (2):-0.379268 AR (3):-0.385193	AR (1): -0.946208 AR (2): -0.142250	AR (1): -0.633296 AR (2): 0.090117 AR (3): -0.436989 AR (4): 0.209000 AR (5): 0.577771 AR (6): 0.081343	AR(1): 1.202031 AR(2): -0.345628 AR(3): -0.709605 AR(4): 1.269134 AR(5): -0.518371
MA coefficients	-	MA(1): 0.871725	MA(1): 0.304895 MA(2): -0.364418 MA(3): 0.323668 MA(4): -0.512626 MA(5): -0.658293	MA(1): -1.320464 MA(2): 0.332046 MA(3): 0.760145 MA(4): -1.338240 MA(5): 0.494523 MA(6): 0.081321
c	0.494186	-0.002238	1.999493	0.499640

Table 6: Breusch-Godfrey Serial Correlation LM Test –Residuals of ARMA model

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
F-statistics	0.551323*	0.322245*	1.380971*	0.967473*
* indicates Null Hypothesis of serial correlation is rejected				

Table 7 ARCH LM Test – Residuals of ARMA model

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
F-statistics	3.044997*	1.915531*	23.79440*	44.11606*
* indicates Null Hypothesis of ARCH effects present is accepted				

Table 8 : Forecasting short-term interest rates using GARCH Model
A. Mean Equation

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
AR coefficients	AR(1):-0.541139 AR(2): -0.368599 AR(3): -0.331692	AR(1) :0.983425 AR(2): -0.184021	AR(1): -0.668224 AR(2): -0.777435 AR(3): -0.274870 AR(4): 0.056349 AR(5): -0.351285 AR(6): 0.029610	AR(1): -1.180118 AR(2): -0.053129 AR(3): 1.026243 AR(4): 0.783246 AR(5): -0.096568
MA coefficients		MA(1): -0.829994	MA(1): 0.742852 MA(2) :0.835649 MA(3): 0.360746 MA(4): -0.013038 MA(5): 0.371521	MA(1): 1.152553 MA(2): -0.271232 MA(3): -1.458300 MA(4): -0.917985 MA(5): 0.309820 MA(6): 0.217210
C	0.495135	0.498968	1.999199	0.499291

B. Variance Equation

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
c	0.001367	0.000768	0.000157	1.84E-05
ARCH (1)	0.288897	0.358242*	0.807274*	0.231832*
GARCH (1)	0.169545	0.094998*	0.154147*	0.740747*
* indicates significant at 1 percent level of significance				

Table 9: ARCH LM test – Residuals of the GARCH model

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
F-statistics	0.034110**	0.072686**	0.240983**	0.562393**
** indicates Null Hypothesis of ARCH effects present is rejected				

Table 10: Forecasting Short-term interest rates using EGARCH model

A. Mean Equation

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
AR coefficients	Ar(1): -0.505682 Ar(2): -0.328716 Ar(3): -0.374026	AR(1): 0.992405 AR(2): -0.180679	AR(1): -0.040858 AR(2): -0.163051 AR(3): -0.213707 AR(4): 0.604353 AR(5): -0.010490 AR(6): -0.041656	AR(1):-0.396294 AR(2): 0.376457 AR(3):-0.338026 AR(4): 0.214620 AR(5):0.377591
MA coefficients		MA(1): -0.845055	MA(1): -0.001634 MA(2) :0.012809 MA(3): 0.021203 MA(4): -0.922794 MA(5): -0.074791	MA(1): 0.389775 MA(2):-0.535445 MA(3):0.158072 MA(4):-0.368689 MA(5):-0.625137 MA(6):-0.006278
C	0.494653	0.498415	2.000325	0.501347
* indicates significant at 1 percent level of significance				

B.Variance Equation

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
C	-0.046298	-7.625553	-1.429152	-4.052075
|RES|/SQR[GARCH](1)	-0.093957*	0.569672*	0.548765*	-0.052435
RES/SQR[GARCH](1)	-0.039618	-0.061218	0.389822*	-0.481201*
EGARCH(1)	0.977840*	-0.070366	0.775322*	0.085803

Table 11: ARCH LM test – Residuals of the EGARCH model

	Commercial Paper returns	Implicit Yield of 91 day Treasury bills returns	Overnight MIBOR returns	Weighted Average Call money returns
F-statistics	0.056434**	0.07966**	0.78783**	0.67393**
** indicates Null Hypothesis of ARCH effects present is rejected				

Table 12 Comparison of models for Commercial Paper

	Random Walk		ARMA		GARCH		EGARCH	
	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
RMSE	0.07729	0.07889	0.06493	0.08006	**0.06206**	0.07656	0.06231	0.07520
MAE	0.06575	0.06375	0.05538	0.06523	0.05370	0.06376	**0.05285**	0.06241
Thiel Coefficient	0.70920	0.86460	0.53946	0.81839	**0.06215**	0.07697	0.06247	0.07563
Bias proportion	0.00651	0.00553	0.03123	0.00683	0.01360	0.00391	0.00957	**0.00316**
Variance proportion	0.39813	0.73394	**0.32189**	0.56461	0.37902	0.76263	0.41805	0.77204
Covariance proportion	0.59535	0.26052	**0.64687**	0.42855	0.60737	0.23345	0.57236	0.22478

Table 13 Comparison of models for Implicit yield on 91-day Treasury bill

	Random Walk		ARMA		GARCH		EGARCH	
	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
RMSE	0.03664	0.03631	0.03630	0.03626	0.03702	0.03586	0.036453	**0.035823**
MAE	0.02129	0.02162	0.02110	0.02158	0.02122	0.02120	**0.020913**	0.021239
Thiel Coefficient	0.92447	0.95064	0.89207	0.94053	0.85591	0.03598	0.036584	**0.035970**
Bias proportion	0.00328	0.00388	0.00476	**0.00283**	0.00586	0.00482	0.004358	0.002871
Variance proportion	0.84727	0.98667	0.79218	0.97905	**0.63812**	0.95382	0.647094	0.954594
Covariance proportion	0.14943	0.00944	0.20304	0.01811	**0.35601**	0.04135	0.348548	0.042536

Table 14 Comparison of models for Overnight MIBOR

	Random Walk		ARMA		GARCH		EGARCH	
	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
RMSE	0.02540	0.02446	**0.02417**	0.02447	0.02481	0.02468	0.03513	0.02519
MAE	0.00671	**0.00629**	0.00885	0.00632	0.00654	0.00647	0.02632	0.00698
Thiel Coefficient	0.83442	0.98246	0.72262	0.96799	0.00620	**0.00617**	0.00873	0.00629
Bias proportion	0.000018	**0.000013**	0.00036	0.000002	0.00026	0.00032	0.47868	0.00216
Variance proportion	0.53053	0.99950	0.40975	0.94118	0.84547	0.96673	**0.10339**	0.61000
Covariance proportion	0.46944	**0.00048**	0.58988	0.05881	0.15426	0.03294	0.41792	0.38783

Table 15 Comparison of models for weighted average Call Money rate

	Random Walk		ARMA		GARCH		EGARCH	
	Static	Dynamic	Static	Dynamic	Static	Dynamic	Static	Dynamic
RMSE	0.02532	0.02528	**0.02404**	0.02525	0.02413	0.02512	0.11803	0.02776
MAE	0.01096	0.01080	0.01164	0.01083	0.01193	**0.01073**	0.11578	0.01264
Thiel Coefficient	0.94248	0.98462	0.76617	0.95953	0.75785	**0.02513**	0.10581	0.02766
Bias proportion	**0.000005**	0.000006	0.00261	0.000059	0.00792	0.00022	0.95554	0.01602
Variance proportion	0.879395	0.99858	0.64017	0.92392	0.63577	0.94855	**0.01926**	0.22902
Covariance proportion	0.12060	0.00141	0.35721	0.07601	0.35630	0.05092	0.02519	**0.75494**

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