

Capturing volatility of stock prices in Dhaka Stock Exchange (DSE)

An approach of non-stochastic volatility models

Md. Mamun Miah¹; Ajit K. Majumder² & Azizur Rahman³

¹M.Sc Student, Department of Statistics, Jahangirnagar University, Savar, Dhaka, Bangladesh

Email: mamunmiah.615@gmail.com

²Professor, Department of Statistics, Jahangirnagar University, Savar, Dhaka, Bangladesh

Email: ajitm@ewubd.edu

³Lecturer, Department of Statistics, Jahangirnagar University, Savar, Dhaka, Bangladesh

Email: rahman.aziz83@gmail.com

Abstract-

Time varying volatility is crucially important in many economic and financial areas. Investors in the stock markets are obviously interested in the volatility of stock prices. High volatility of return in financial market may discourage investors to invest in stock market and hence greater uncertainty. So we need to estimate the appropriate volatility model to capture the volatility. This study applies five time series forecasting volatility models such as Random Walk (RW), Historical Average (HA), Moving Average (MA), Exponential Smoothing (ES), Autoregressive Process (AP) and Simple Regression (SR) respectively to four selected companies of DSE. Result shows that in all four companies RW model capture volatility quite well among other competing models.

Keywords-

Volatility, closing price, return, volatility models.

1. Introduction

The financial market is a part of a market system. Financial markets play an important role in the process of economic growth and development by facilitating saving and channeling funds from the savers to investors. The main participants in financial market transactions are households, business (including financial institutions), and government that purchase or sell financial assets. An

improvement aspect of modern financial markets is absolute judgment of the stock markets that's why stock market plays an important role in the economy of a country which indicates stock market is one of the most important sources for companies to raise money. Stock markets play tends to be very efficient in the allocation of capital to its highest-value users. These markets also help increase savings and investment, which are essential for economic development. However, volatility and market efficiency are two important features, which will ultimately determine the effectiveness of the stock market in economic development. Different financial variables in stock market such as stock price, share index etc. This share prices may fall in some situation and may constant or rise in another situation. These move up or down are termed as volatility. A volatile stock would be one that sees very large swings in its stock price. If there is a high volatility in the stock market i.e., the market is not in consistent position and the country's economy will be threatened which would lead investors to demand a high- risk premium, creating highest cost of capital, impedes investment and slows economic development [5]. Volatility is itself a stock variable, having to be measured over a period of time, rather than a flow variable, measurable at any instant of time. Observed volatility has to be observed over stated periods of time, such as hourly, daily, or weekly (say).

In financial data we are mainly concern with the variability of stock price. A fall in a stock market will weaken consumer confidence and thus drive consumer spending [8]. The stock market is one of the most important sources for companies to raise money. This allows businesses to be publicly traded, or raise additional capital for expansion by selling shares of ownership of the company in a public market. Time series models have been widely used in many disciplines in the science. The time series models with changing variance over time which is shown by most of the financial data. Such time series models with heteroscedastic errors are specifically useful for modeling high frequency data like stock returns and exchange rates.

In this study, volatility models are analyzed for the selected companies of DSE and suitable volatility models are constructed in order to see which one is better in modeling the time-varying volatility. In section two, we describe some preliminaries related to volatility, standard deviation and risk. Section 2 defined some stylized facts about financial market volatility. Section 3 depicts different time series volatility forecasting models. Also clear description of forecasting models based on past standard deviation is discussed. Section 4 indexed the data used in this study. Section 5 presents results and description of this study. Finally we made a conclusion with fair recommendation. An appendix consists on the related formulas for different time series forecasting models used in this study.

2. Financial Market Volatility with Some Preliminaries

Volatility, Standard Deviation and Risk

Many investors and generations of finance students often have an incomplete appreciation of the differences between volatility, standard deviation, and risk. It is worth elucidating some of the conceptual issues here. In finance, volatility is often used to refer to standard deviation, σ , or variance, σ^2 , computed from a set of observations as

$$\hat{\sigma}_t^2 = \frac{1}{N-1} \sum_{t=1}^N (R_t - \bar{R})^2$$

Where \bar{R} is the mean return. The sample standard deviation statistic $\hat{\sigma}$ is a distribution free parameter representing the second moment characteristic of the sample. Only where σ is attached to a standard distribution, such as a normal or a t distribution, can the required probability density and cumulative probability density be derived analytically. Indeed σ can be calculated from any irregular shape distribution, in which case the probability density will have to be derived empirically. In the continuous time setting, σ is a scale parameter that multiplies or reduces the size of the fluctuations generated by the standard wiener process. Depending on the dynamic of the underlying stochastic process and whether or not the parameters are time varying, very different shapes of returns distributions may result. So it is meaningless to use σ as a risk measure unless it is attached to a distribution or a pricing dynamic. When σ is used to measure uncertainty, the users usually have in mind, perhaps implicitly, a normal distribution for the return distribution [11].

Standard deviation, σ , is the correct dispersion measure for the normal distributions, but not all. Other measure that have been suggested and found useful include the mean absolute return and the inter-quartile range. However, the link between volatility and risk is tenuous; in particular, risk is more often associated with small or negative returns, whereas most measures of dispersion make no such distinction. The sharp ratio, for example, defined as return in excess of risk free rate divided by standard deviation, is frequently used as an investment performance measure. It incorrectly penalizes occasional high returns. The idea of “semi variance,” an early suggestion by Harry Markowitz (1991)[9], which only uses the squares of returns below the mean, has not been widely used, largely because it is not operationally easy to apply in portfolio construction.

3. Methods and Materials

3.1 Models Used in Volatility Forecasting

In this section, we first describe various popular time series volatility models that use the historical information set to formulate volatility forecasts and a

second approach that derives market estimates of future volatility from traded option prices. Non parametric methods for volatility forecasting have been suggested. But, as non-parametric methods were reported to perform poorly (Pagan and Schwert 1990; and Kenneth West and Dongchul Cho 1995) [10, 13], they will not be discussed here and volatility models that are based on neural networks (Michael Hu and Christ Tsoukalas 1999; genetic programming, e.g. Zumbach, Pictet, and Masutti 2001; time change and duration, e.g. Cho and frees 1988, and Engle and Rusell) [6, 14, 4].

3.2 Time series volatility forecasting models

Stephen Brown (1990) [2], Engle (1993), and Abdurrahman Aydemir (1998) [1] contain lists of time series models for estimating and modeling volatility. Kroner (1996) [13] explains how volatility forecasts can be created and used. The specification of volatility models are provided in appendix A. all models described in this section capture volatility persistence or clustering. Others take into account volatility asymmetry also. It is quite easy to construct a supply and demand model for financial assets, with supply a constant and demand partly driven by an external instrument that enters nonlinearity that will produce a model for financial returns that is heteroscedastic. Such a model is to some extent “theory based” but is not necessarily realistic. The pure time series models discussed in this section are not based on theoretical foundations but are selected to capture the main features of volatility found with actual returns. If successful in this, it is reasonable to expect that they will have some forecasting ability.

3.3 Prediction Based on Past Standard Deviations

This group of models starts on the basis that $\sigma_{t-\tau}$ for all $\tau > 0$ is known or can be estimated at time $t - 1$. The simplest historical price model is the random walk model, where σ_{t-1} is used as a forecast for σ_t . Extending this idea, we have the historical average method, the simple Moving Average method, the exponential Smoothing method and the Exponentially Weighted Moving Average method.

The historical average method makes use of all historical standard deviations while the Moving Average method discards the older estimates. Similarly, the Exponential Smoothing method uses all historical estimates, and the Exponentially Weighted Moving Average (EWMA) method uses only the more recent ones. But unlike the previous two, the two exponential methods place greater weights on the more recent volatility estimates. All together, the four methods reflect a tradeoff between increasing the number of observations and sampling nearer to time t .

The *RiskmetricsTM* model uses the EWMA method. The Smooth Transition Exponential Smoothing model, proposed by James Taylor (2001) [12], is a more flexible version of exponential smoothing where the weight depends on the size, and sometimes the size as well, of the previous return. Next we have the Simple Regression method that express volatility as a function of its past values and an error term. The Simple Regression method principally autoregressive. If past volatility errors are also included, one gets the ARMA model for volatility. Introducing a differencing order $I(d)$, we get ARIMA when $d=1$ and ARFIMA when $d<1$. Finally, we have the Threshold Autoregressive model, where the thresholds separate volatility into states with independent simple regression models and noise processes for volatility in each state.

Apart from Random walk and Historical Average, successful applications of models described in this section normally involve searching for the optimal lag length or weighting scheme in an estimation period for out-of-sample forecasting. Such optimization generally involves minimizing in-sample volatility forecast errors. A more sophisticated forecasting procedure would involve constant updating of parameter estimates when new information is observed and absorbed into the estimation period.

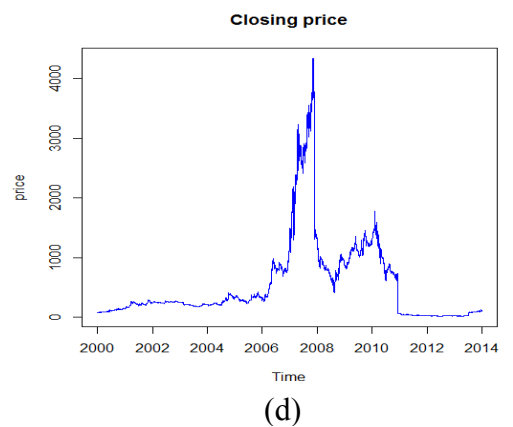
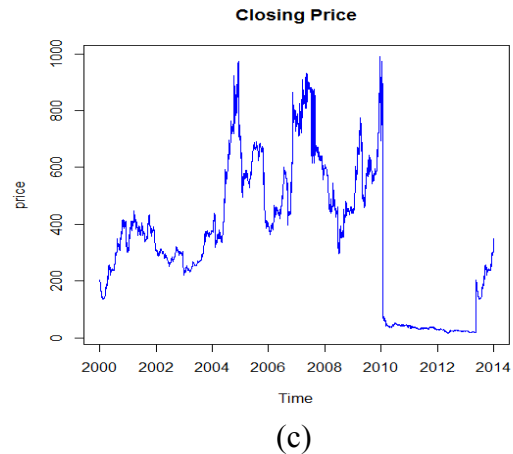
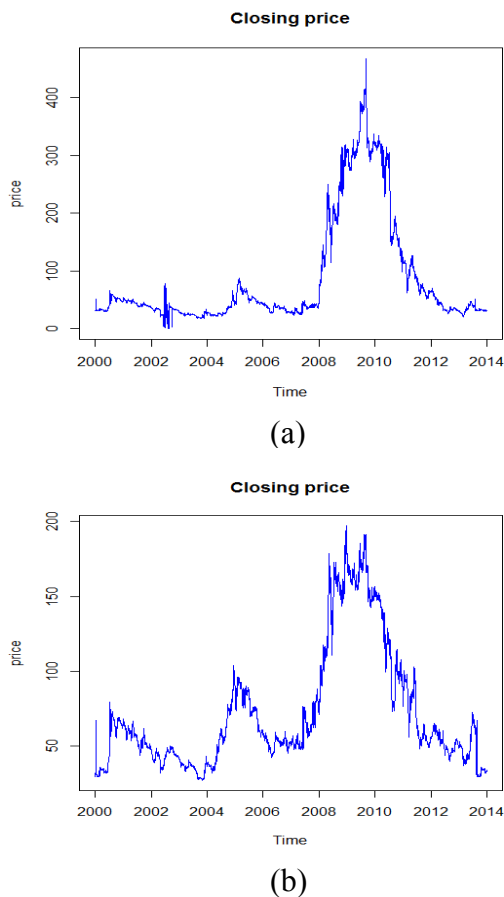
4. Data

For developing the country we have to analyze the financial data as like stock market data. In Bangladesh there are two stock exchange such as i) Dhaka Stock Exchange (DSE) and ii) Chittagong Stock Exchange. But the market behavior of two

stock exchanges is almost similar. That's why for this study we collect information including closing price of selected stocks consider here from the DSE library. We use both daily and monthly closing price of the selected four companies as Bangladesh Export Import Company Limited (BEICL), Beximco Pharmaceuticals Limited (BPL), Prime Bank Limited (PBL) and Arab Bangladesh Bank Limited (ABBL) from January, 2000 to November, 2014 for time series analysis, measuring and forecasting the volatility models.

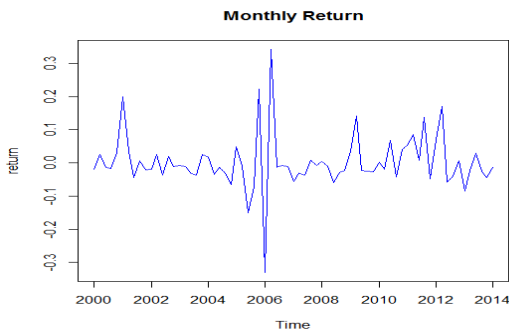
5. Results and Discussion

Figure 1: Time series plot of closing price of the selected companies

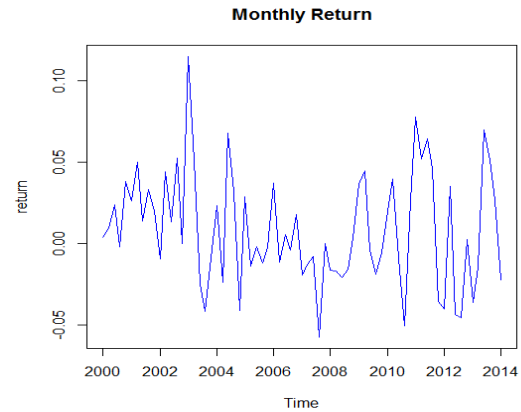


From the above time series plot, we observe that over the period of study the time series data seems to be trending, suggesting perhaps that the mean and variance has been changing. So we can say that the daily data of closing price of Bangladesh Export Company (a), Beximco Pharmaceuticals Ltd. (b), Prime Bank Ltd. (c) and AB Bank Limited (d) of Dhaka Stock Exchange is not stationary. It is visual that the mean and variance is not remains constant from time to time, so we can say that the daily data of closing price is not stationary.

Figure 2: Time Series Plot of monthly return series

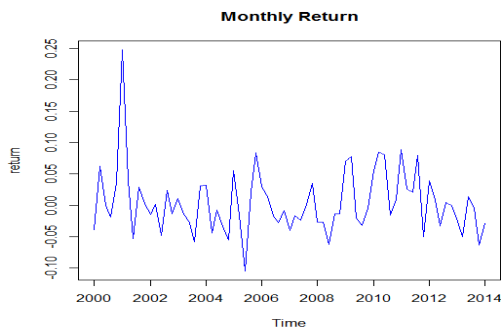


BEICL



AB Bank

From the above graph we observe that a large spikes for BEICL at the year 2006 and for the remaining three companies there are some ups and downs of monthly return at the whole time periods.



BPL

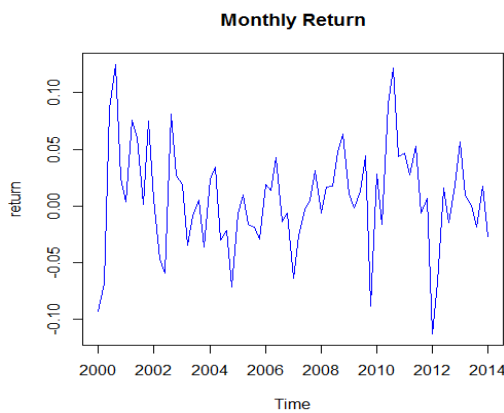


Table 1: Descriptive Statistics of different companies

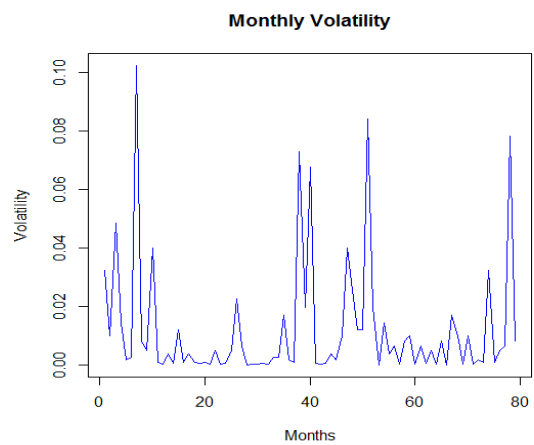
	BEICL	BPL	PBL	ABBL
Mean	0.0003927	0.001541	-0.0057480	-0.002609
Median	-0.0113700	-0.004963	-0.0002313	-0.002173
Maximum	0.3424000	0.248000	0.1594000	0.163100
Minimum	-0.3296000	-0.128000	-0.6219000	-0.998600
Std. Deviation	0.074096944	0.047749342	0.0768267	0.05927684
Kurtosis	5.628480769	3.767200067	33.00541145	68.0740918
Skewness	0.915266577	1.010485147	-4.511147879	-6.84981819

From the above table we observe that for every company kurtosis value is greater than 3. Hence we can say that the return series has leptokurtic distribution.

Table 2: Shapiro- Wilk Normality test

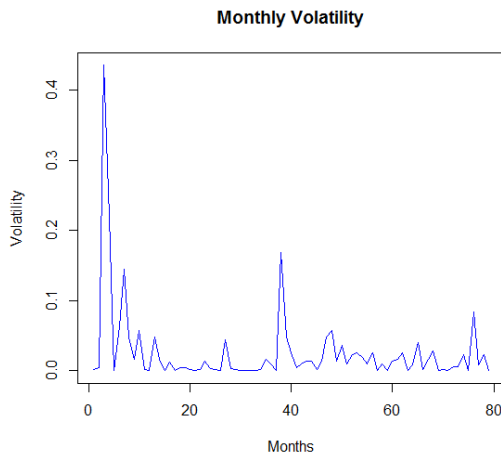
Company Name	Statistics (<i>W</i>)	Significant <i>P – Value</i>
BEICL	0.878	7.513×10^{-11}
BPL	0.9439	1.856×10^{-06}
PBL	0.6548	$< 2.2 \times 10^{-16}$
ABBL	0.5161	$< 2.2 \times 10^{-16}$

From the above Shapiro-Wilk normality test we observe that for each company p value is approximately zero i.e. it's value is less than 0.05 that leads null hypothesis is rejected. So we can say that the return series is non-normal which support descriptive statistic returns.

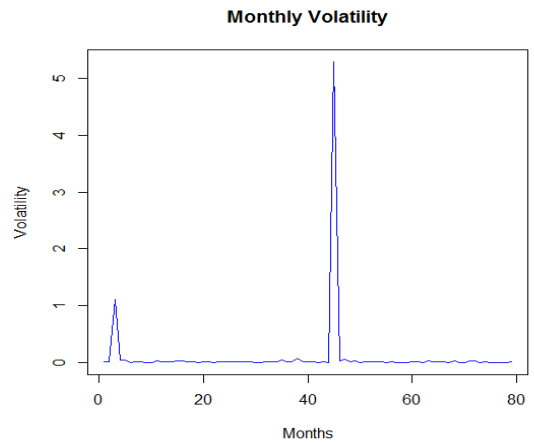


BPL

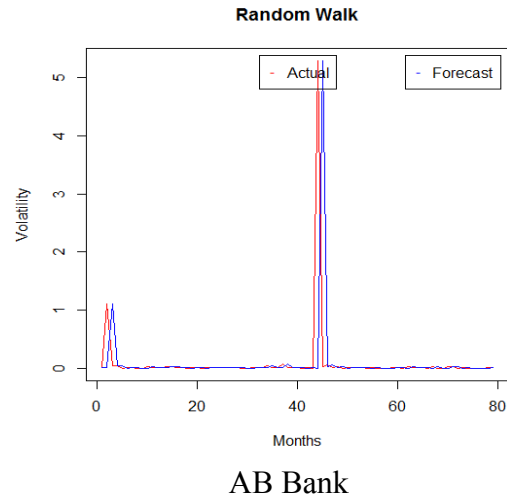
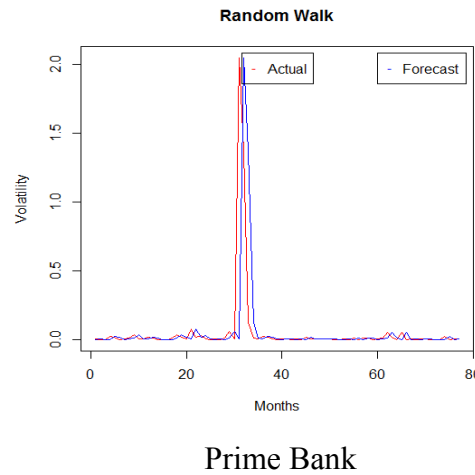
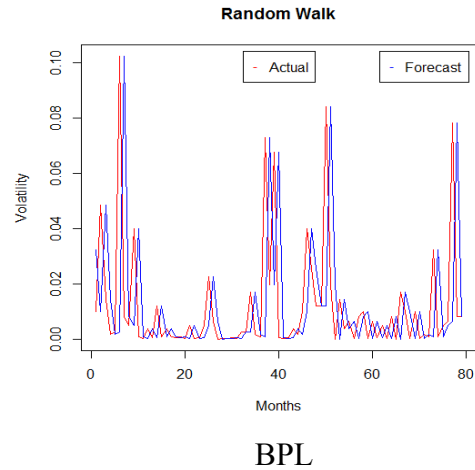
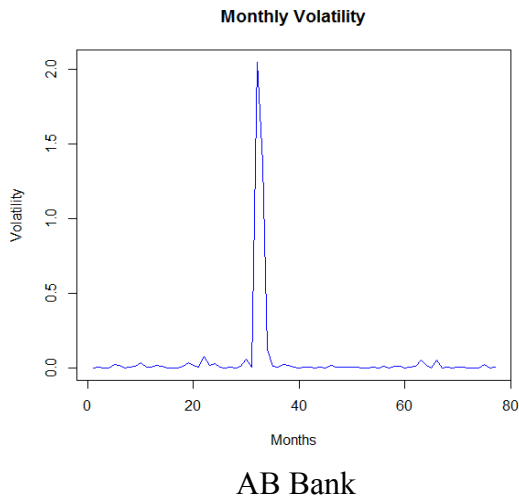
Figure 3: Monthly Volatility of the selected companies



BEICL



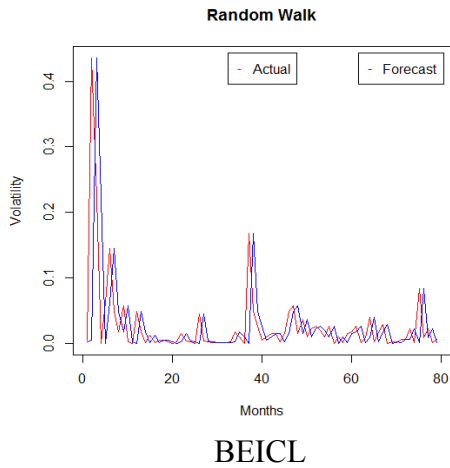
Prime Bank



From the above figure we observe that for BEI Company there is a high volatility at the beginning of the data series and there are a series of high volatility at different months for Beximco Pharmaceuticals but there is a large spike at 31 months and 43 months respectively for Prime Bank and AB Bank.

Figure 4: Volatility forecasting models

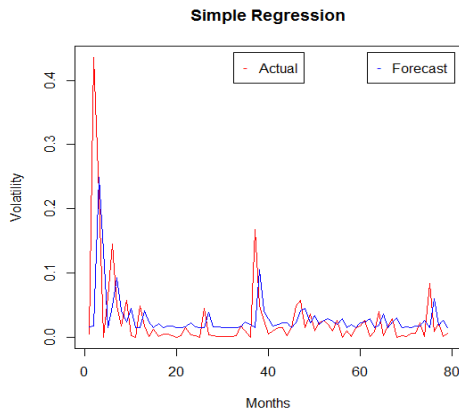
1. Random Walk Model



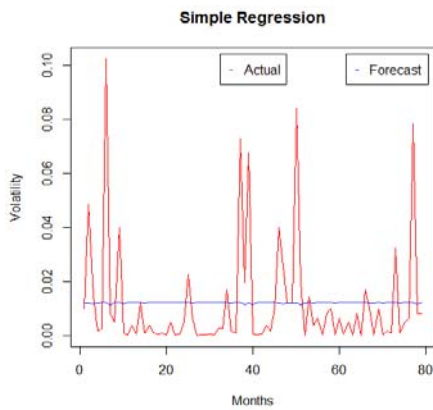
From the above figure we can see that, for BEI company there is a high volatility at the beginning of the data series compared to last months. But on the other hand for Beximco Pharmaceuticals there are a series of high volatility in different months. At the same time we observe that for Prime Bank and AB Bank only a few spike of value is present. For RWM

actual and forecasted volatilities are much closure and hence this model fits well.

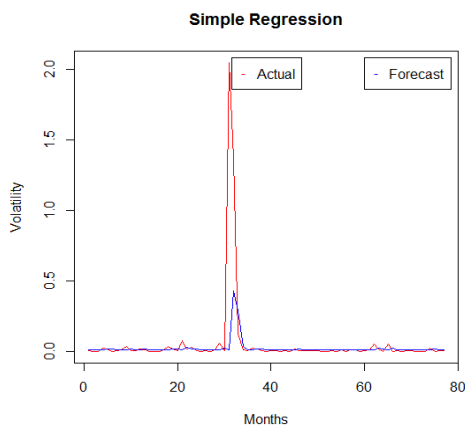
2. Simple Regression Model



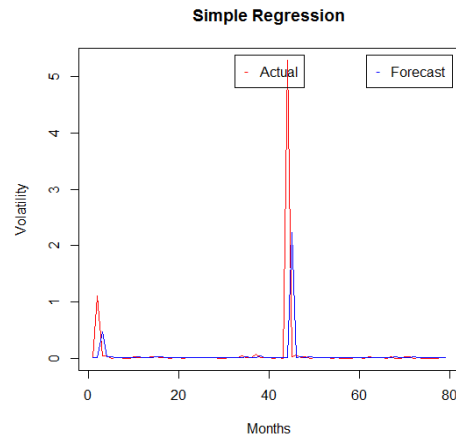
BEICL



BPL



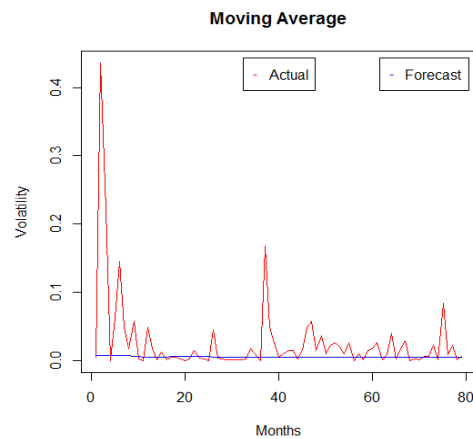
Prime Bank



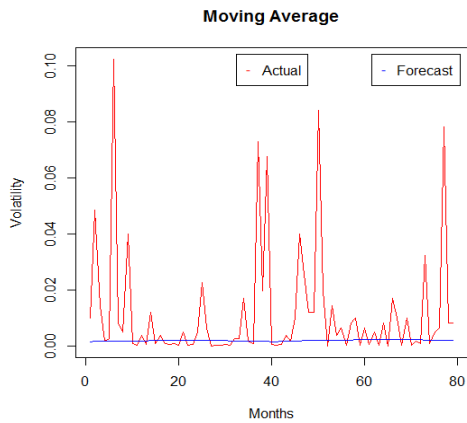
AB Bank

From the above figure we can see that, for BEI company there is a high volatility at the beginning of the data series compared to last months. But on the other hand for Beximco Pharmaceuticals there are a series of high volatility in different months for actual value but not for forecasted value. At the same time we observe that for Prime Bank and AB Bank only a few spike of value is present. Simple Regression doesn't forecast volatility well.

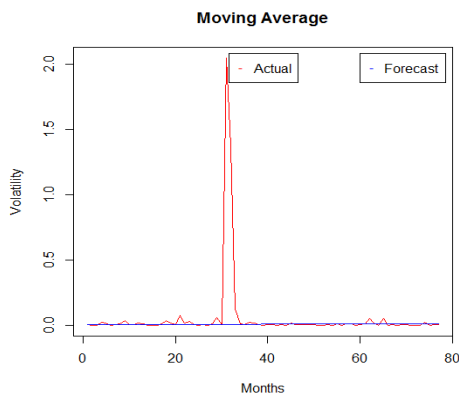
3. Moving Average



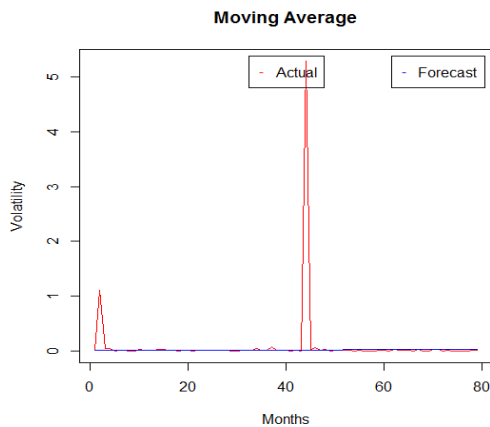
BEICL



BPL



Prime Bank

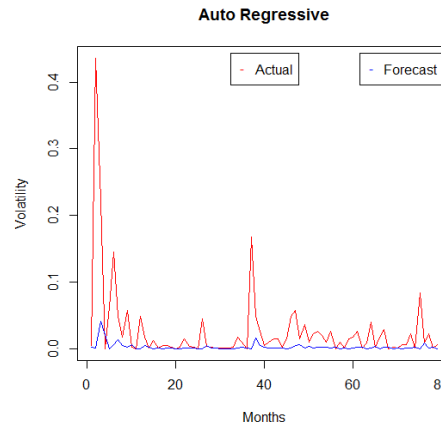


AB Bank

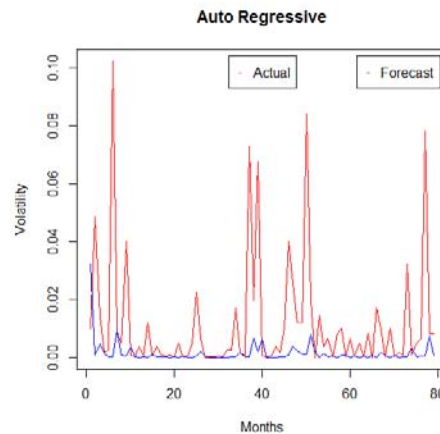
From the above figure we can see that, for BEI company there is a high volatility at the beginning of the data series compared to last months for actual value. But on the other hand for Beximco Pharmaceuticals there are a series of high volatility in different months. At the same time we observe that for Prime Bank and AB Bank only a few spike of value is present. For forecasted value we observe that

the forecasted line is showing around zero volatility and this model doesn't forecast volatility well.

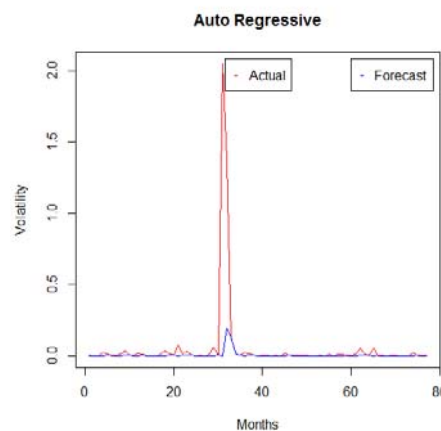
4. Auto Regressive



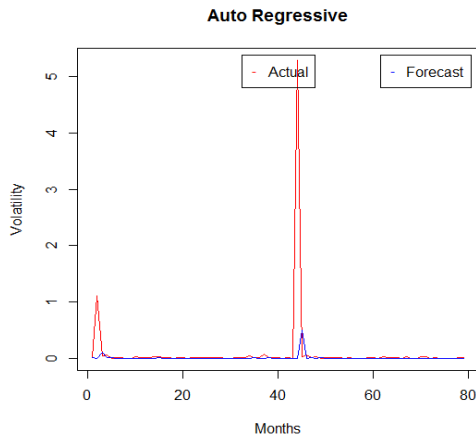
BEICL



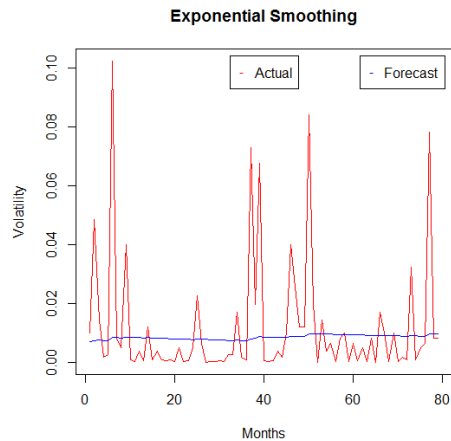
BPL



Prime Bank



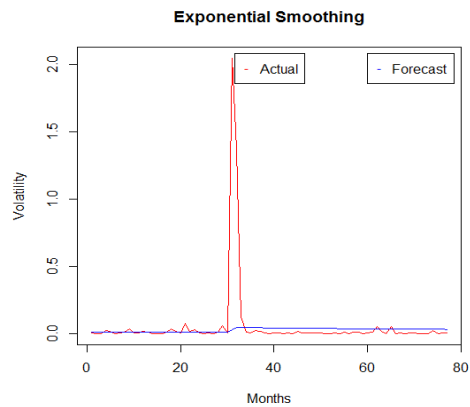
AB Bank



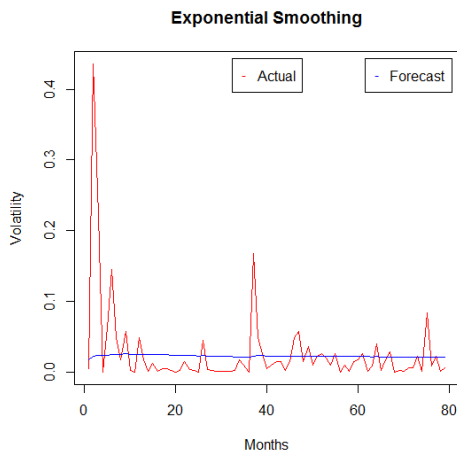
BPL

From the above figure we can see that, for BEI company there is a high volatility at the beginning of the data series compared to last months. But on the other hand for Beximco Pharmaceuticals there are a series of high volatility in different months. At the same time we observe that for Prime Bank and AB Bank only a few spike of value is present for actual value. But for forecasted value we observe that the forecasted line fluctuates around zero volatility.

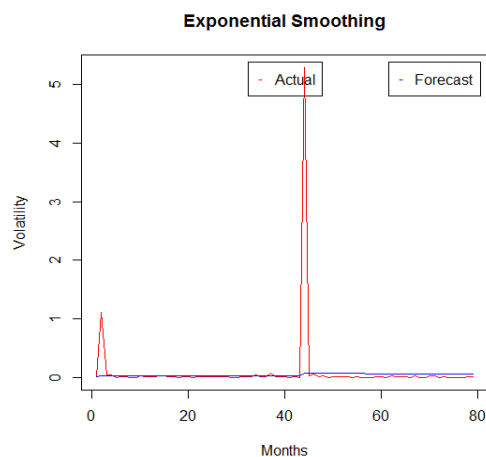
5. Exponential Smoothing



Prime Bank



BEICL

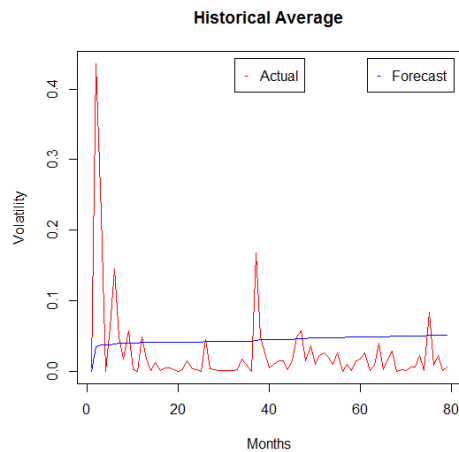


AB Bank

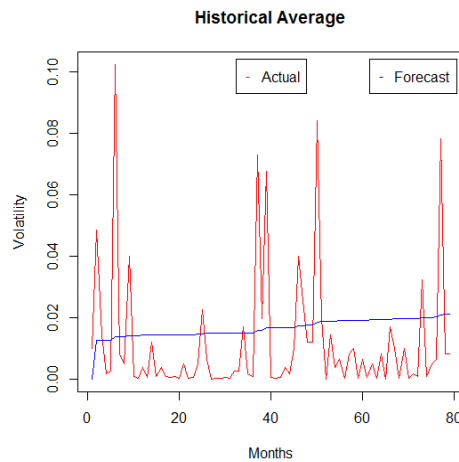
From the above figure we can see that, for BEI company there is a high volatility at the beginning of the data series compared to last months. But on the other hand for Beximco Pharmaceuticals there are a series of high volatility in different months. At the same time we observe that for Prime Bank and AB

Bank only a few spike of value is present. But for forecasted volatility we observe that there is no fluctuation pattern for any company. So exponential Smoothing Method doesn't forecast volatility well for our data series.

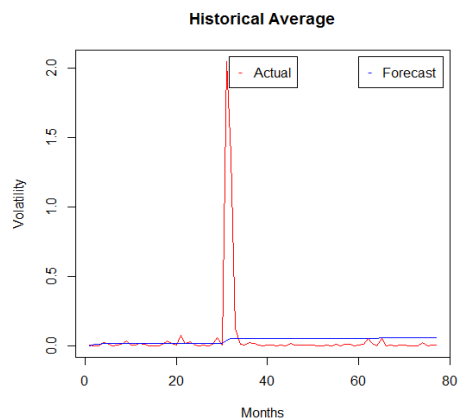
6. Historical Average



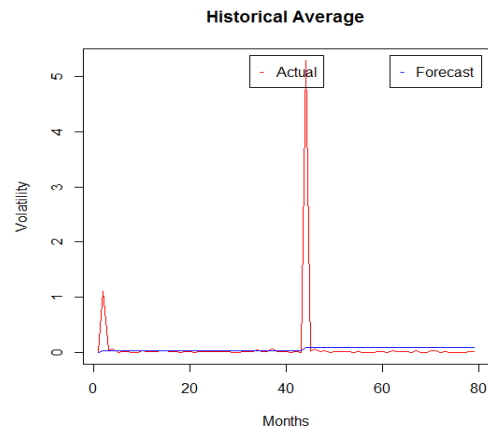
BEICL



BPL



Prime Bank



AB Bank

From the above figure we can see that, for BEI company there is a high volatility at the beginning of the data series compared to last months. But on the other hand for Beximco Pharmaceuticals there are a series of high volatility in different months. At the same time we observe that for Prime Bank and AB Bank only a few spike of value is present. But for forecasted volatility we observe that a fractional increase of monthly volatility for BEICL and BPL. On the other hand, around zero volatility is noticed for Prime Bank and AB Bank Limited.

5. Conclusion

Knowledge about a financial market is very essential for investors to invest money or purchase share from the stock market. If we can understand what is happening to a stock market, we take our chances to make the right decision at the right time. But evaluation of financial markets is complicated in real world because well-documented volatility modeling is difficult to predict. Volatility is the degree to measure the risk and return behavior of developed as well as developing country. Especially those countries where the opportunity of investment is very little. Time varying volatility is crucially important in certain economic and financial contexts. So in this study our object is to forecast the future volatility by the best model and observe the future phenomena of different company's volatility of Bangladesh Stock Market. In order to forecast the volatility of the individual stocks stochastic and non-stochastic volatility models are used.

In this study representation of monthly return series of selected companies reveals that the volatility or variability of the data changes over time that means the data shows volatility clustering. From the descriptive statistics of return series we can say that the return series of all selected companies has leptokurtic distribution. We test the return series and use the Q-Q plot which gives conclusion of non-normality of return series. We use the simple forecasting models in which random walk model gives the better forecast for monthly volatility of selected companies.

Appendix A

Volatility models for Historical Price

A.1 Prediction models based on sample standard deviations

Sample standard deviation of period t returns represents volatility, σ_t and $\hat{\sigma}_t$ is the forecast of σ_t . If t is a month then σ_t is often calculated as the sample standard deviation of all daily returns in the month. If t is a day then σ_t is defined by daily squared return for a long time. Daily σ_t is derived from the cumulation of intraday returns with the availability of high frequency data.

Random Walk (RW)

$$\hat{\sigma}_t = \sigma_{t-1}$$

Historical Average (HA)

$$\hat{\sigma}_t = (\sigma_{t-1} + \sigma_{t-2} + \dots + \sigma_1) / (t-1)$$

Moving Average (MA)

$$\hat{\sigma}_t = (\sigma_{t-1} + \sigma_{t-2} + \dots + \sigma_{t-\tau}) / \tau$$

Exponential Smoothing (ES)

$$\hat{\sigma}_t = (1 - \beta)\sigma_{t-1} + \beta \hat{\sigma}_{t-1} \text{ and } 0 \leq \beta \leq 1$$

Simple Regression (SR)

$$\hat{\sigma}_t = \gamma_{1,t-1}\sigma_{t-1} + \gamma_{2,t-1}\sigma_{t-2} + \dots$$

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