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MODELING VOLATILITY IN STOCK MARKET INDICES: THE CASE OF DHAKA STOCK EXCHANGE (DSE)

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Abstract

Measuring and forecasting stock price volatility is one of the basic demand for any risk-averse investors for its significant implication in detecting and predicting time varying shocks in stock prices. This paper is an attempt to measure as well as forecast return volatility in stock prices at Dhaka Stock Exchange (DSE). Daily return data from 28th January, 2013 to 30th November, 2016 have been used for the three different stock indices (i.e. DS 30, DSEX, and DSES) and GARCH (1, 1) test has been applied for measuring the statistically significant presence of volatility. This test reveals less volatility in stock returns indicated by lack of statistically significant heteroscedasticity in the residuals of all these return data series. Forecasted volatility have also found to be decreasing in the same sample data. This result is an evident of less trading activity by the investors during the sample period.

Key words: Volatility, Heteroskedasticity, ARCH, GARCH

1. Introduction

Volatility model is considered as the central requirement in almost all financial applications. Engle and Pattern (2001) has rightly stated the diverse use of volatility model as,

> "A volatility model should be able to forecast volatility. Typically a volatility model is used to forecast the absolute magnitude of returns, but it may also be used to predict quantiles or, in fact, the entire density. Such forecast are used in risk management, derivative pricing and hedging, market making, market timing, portfolio selection and many other financial activities."

Stock price behavior has long been of interest to researchers, economists and investors because of its implications on capital formation, wealth distribution and investors' rationality. Financial economists agree about the facts that the asset prices are volatile and that the volatility and returns are predictable over time. Although the sources of volatility are frequently found to be elusive, the role played by various information is of paramount importance (Ahmed, M. F. 2002). Due to the last two stock market debacles in 1996 and 2010, investors at Dhaka Stock Exchange (DSE) were struggling for a long time to gain confidence regarding investment in stocks. Still now, there is little evidence to believe that DSE will come back with its full rhythm with increased frequency of trading securities that ensure efficient allocation of long term funds among different firms and industries. But there is no doubt that an active and efficient stock market is a pre-requisite for macroeconomic expansion and industrial growth (Ahmed, M. F. 2000). A sound flow of funds through the use of stock market activity not only brings the listed firms in line with innovative production opportunities but also enhances favorable changes in the economy's

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balance of trade (BOT), improves household earnings, consumption and savings that ultimately leads to have an increased economic growth for the country. One of the most important reasons for which DSE has been experiencing frequent price abnormality is very little dependency from the investors' side on fundamental performance parameters of individual firms which essentially requires an in-depth analysis of risk-return characteristics of securities in the exchange. Investment decisions are generally based on the trade-off between risk and return; the econometric analysis of risk is therefore an integral part of asset pricing, portfolio optimization, option pricing and risk management (Engle. R, 2001). The three main purposes of forecasting volatility are for risk management, for asset allocation, and for taking bet son future volatility. A large part of risk management is measuring the potential future losses of a port folio of assets, and in order to measure these potential losses, estimates must be made of future volatilities and correlations. In asset al location, the Markowitz approach of minimizing risk for a given level of expected returns has become a standard approach, and of course an estimate of the variance-covariance matrix is required to measure risk. Perhaps the most challenging application of volatility forecasting, however, is to use it for developing a volatility trading strategy (Reider, R. 2009). This study is an attempt to deal to risk management in the portfolio through the application of modeling and structuring volatility in stock returns at Dhaka Stock Exchange (DSE). Three different stock returns (i.e. DS 30, DSEX, and DSES) of Dhaka Stock Exchange (DSE) have been initially selected for the presence of ARCH effect in their return series as well as modeling volatility in returns. In this case, in spite of having few deficiencies, GARCH (1, 1) model is highly recommended tool for capturing as well as estimating the volatility in the return series.

2. Objectives of the Study

The relationship between the stock market returns and their volatilities is a subject of considerable research interest. The daily information shocks, as well as the differences in investor opinions and expectations are source of stock market volatility. A significant rise in stock market volatility, due to positive and negative information shocks, reduces market efficiency and liquidity (Mishra. B & Rahman. M 2010). This study has attempted to identify and estimate the presence of volatility in three different stock returns (i.e. DS 30, DSEX, and DSES) in Dhaka Stock Exchange (DSE) with the application of GARCH (1, 1) model. Daily index data from 28th January, 2013 to 30th November, 2016 have been selected for DS 30 and DSEX index. On the other hand, daily index data from 20th January, 2014 to 30th November, 2016 has been chosen for DSES index. The present study is intended to investigate and identify the following issues:

Whether there exists any statistically significant presence of volatility as measured by Autoregressive Conditional Hetroskedasticity (ARCH) model and Generalized Autoregressive Conditional Hetroskedasticity (GARCH) model;

To forecast volatility clusters exhibited by three different stock indexes in Dhaka Stock Exchange (DSE) Limited.

3. Dhaka Stock Exchange Indexes: A Brief Overview

At Present, Dhaka Stock Exchange (DSE) computes three indices: DSE Board Index (DSEX); DSE 30 Index (DS 30), and DSEX Shariah Index (DSES). None of these DSE indices include mutual funds, debentures, and bonds. The Dhaka Stock Exchange Limited introduced DSEX and DS 30 indices as per DSE Bangladesh Index Methodology designed and developed by S&P Dow Jones Indices with effect from January 28, 2013. DSEX is the Board Index of the Exchange (Benchmark Index) which reflects around 97 percent of the total equity market capitalization. On the other hand, DE30 constructed with 30 leading companies which can be said as investable Index of the Exchange. DS30 reflects around 51 percent of the total equity market capitalization. On the other hand DSEX Shariah Index known as DSES provides broad market coverage of shariah-compliant equities listed on the DSE. All these three indices are computed based on float-adjusted market capitalization. Table: 1 depicts the descriptive statistics of the three selected stock returns between January 28, 2013 and November 30, 2016. It has been observed that the mean return is highest and standard deviation is the lowest for DSES returns. The negative values of skewness for DS 30 and DSEX returns implies that these return have a long left tail and long right tail has been found for DSES returns. The kurtosis values of all these stock returns explain that they are all leptokurtic. Finally, the probabilities of Jarque-Bera statistics fails to accept the null hypothesis of normality in all the return series.

Table 1: Descriptive Statistics of Three Different Index Returns at DSE

Descriptive Statistics	DS 30 Returns	DSEX Returns	DSES Returns
Mean	0.019926	0.014178	0.026553
Std. Dev.	1.014164	0.928080	0.758752
Skewness	-0.027088	-0.114359	0.330195
Kurtosis	6.075084	5.959360	3.745097
Jarque-Bera	322.0028	299.5441	24.24521
Probability	0.000000	0.000000	0.000005
Observations	817	817	587

Note: Author’s Own Calculation

4. Review of Literature

Stock price volatility is an extremely important concept in finance especially for its association with informational as well as allocational efficiency of the stock market. On the other hand, the dynamics of stock prices behavior is an accepted phenomenon and all market participants including regulators, professionals, and academic have consensus about it. But what causes stock price volatility is a question that remains unsettled. However, researcher in quest of answer this question has investigated stock price volatility from different angles. In this regards, from the twentieth century and particularly after introducing ARCH model by Engle (1982), extended by Bollerslev (1986) and Poon and Granger (2003) several hundred research that mainly accomplished in developed economy and to some extent in developing economy has been done by researchers using different methodology. This section will give the reader a glimpse of these studies as follows:

Engle (1982) published a paper that measured the time-varying volatility. His model, ARCH is based on the idea that a natural way to update a variance forecast is to average it with the most recent squired 'surprise' (i.e. the squared deviation of the rate of return from its mean). While conventional time series and econometric models operate under an assumption of constant variance, the ARCH process allows the conditional variance to change over time as a function of past errors leaving the unconditional variance constant. In the empirical application of ARCH model a relatively long lag in the conditional variance equation is often called for, and to avoid problems with negative variance parameters a fixed lag structure is typically imposed.

Bollerslev, T. (1986) to overcome the ARCH limitations in his model, GARCH thatgeneralized the ARCH model to allow for both a longer memory and a more flexible lag structure. In the ARCH process the conditional variance is specified as a linear function of past sample variance only, whereas the GARCH process allows lagged conditional variances to enter in the model as well.

Engle, Lilien, and Robins (1987) introduced ARCH-M model by extending the ARCH model to allow the conditional variance to be determinant of the mean. Whereas in its standard form, the ARCH model expresses the conditional variance as a linear function of past squared innovations. In this new model they hypothesized that, changing conditional variance directly affect the expected return on a portfolio. Their result from applying this model to three different data sets of bond yields are quite promising. Consequently, they include that risk premia are not time invariant; rather they vary systematically with agents' perceptions of underlying uncertainty.

Nelson (1991) extended the ARCH framework in order to better describe the behavior of return volatilities. Nelson's study is important because of the fact that it extended the ARCH methodology in a new direction, breaking the rigidness of the GARCH specification. The most important contribution was to propose a model (EARCH) to test the hypothesis that the variance of return was influenced differently by positive and negative excess returns. His study found that not only was the statement true, but also that excess returns were negatively related to stock market variance.

Glosten, Jagannathan and Runkle (1993), to modify the primary restrictions GARCH-M model based upon the truth that GARCH model enforce a systematic response of volatility to positive and negative shocks, introduced GJR's (TGARCH) model. They conclude that there is a positive but significant relation between conditional mean and conditional volatility of the excess return on stocks when the standard GARCH-M framework is used to model the stochastic volatility of stock returns. On the other hand, Campbell's Instrumental Variable Model estimates a negative relation between conditional mean and conditional volatility. They empirically show that the standard GARCH-M model is misspecified and alternative specification provide reconciliation between these two results. When the model is modified to allow positive and negative unanticipated returns to have different impacts on conditional variance, they found that a negative relation between the conditional mean and the conditional variance of the excess return on stocks. Finally, they also found that positive and negative unexpected returns have vastly different effects on future conditional variance and the expected impact of a positive unexpected return is negative.

Engle and Ng (1993) measure the impact of bad and good news on volatility and report an asymmetry in stock market volatility towards goods news as compared to bad news. More specifically, market volatility is assumed to be associate with arrival of news. A sudden drop in price is associated with bad news. On the other hand, a sudden rise in price is said to be due to good news. Engle and Ng found that bad news create more volatility than goods news of equal importance. This asymmetric characteristics of market volatility has come to be known as ‘leverage effect’. Engle and Ng (1993) provide new diagnostic tests and models, which incorporate the asymmetry between the type of news and volatility, they advised researchers to use such enhanced models when studying volatility.

Batra (2004) in an article entitled “Stock Return Volatility Pattern in India” examine the time varying pattern of stock return volatility and asymmetric GARCH methodology. He also examined sudden shifts in volatility and the possibility of coincidence of these sudden shifts with significant economic and political events of both domestic and global origin. Kumar (2006) in his article entitled “Comparative Performance of Volatility Forecasting Models in Indian Markets” evaluated the comparative ability of different statistical and economic volatility forecasting models in the context of Indian stock and forex market. Banerjee and Sarkar (2006) examined the presence of long memory in asset returns in the Indian stock market. They found that although daily returns are largely uncorrelated, there is strong evidence of long memory in its conditional variance. They concluded that FIGARCH is the best fit volatility model and it outperforms other GARCH type models. They also observed that the leverage effect is insignificant in Sensex returns and hence symmetric volatility models turn out to be superior as they expected.

Mishra. B, & Rahman. M., (2010) have examined the dynamics of stock market returns volatility of India and Japan. The author found that the stock market returns of India are more predictable based on the lagged realized rates of return than those of Japan. The estimate of the mean-model show ARCH component in India’s stock market while that was not found in Japanese stock market. Finally they have stated that there are more evidence of asymmetric effects of bad news and good news on both stock market returns.

Goudarzi. H, (2010) have used BSE500 stock index to examine the volatility in Indian Stock Market and its related stylized facts using two commonly used symmetric volatility models: ARCH and GARCH. The adequacy of the selected models has been tested using ARCH-LM test and LB statistics. The study concludes that GARCH (1, 1) model explains volatility of the Indian Stock Market and its stylized facts including volatility clustering, fat tail and mean reverting satisfactorily.

Rahman and Moazzem (2011) have attempted to identify causal relationship between the observed volatility in Dhaka Stock Exchange (DSE) and the correcponding regulatory decision taken by Security and Exchange Commission (SEC). Vector Autoregressive (VAR) Model has been used in that study that provides a statistically significant relationship between decision taken by the regulatory authority and the market volatility. Based on this findings, it is concluded that the major indicators of DSE is becoming more volatile over time and the regulators are not efficient enough to guard this volatility.

Chand. S, Kamal. S, Ali. I. (2012) have applied ARIMA-GARCH type models to identify and estimate the mean and variance components of the daily closing price of the Muslim Commercial Bank at Pakistan. They have attempted to explain the volatility structure of the residuals through the use of the above said models. They have concluded that ARCH (1) model has failed to fully capture the ARCH effect from the residuals generated by the mean equation. The GARCH (1,1) model has fully captured the ARCH effect and it has better ability of capturing the volatility clustering among all estimated ARCH-type models.

Aziz and Uddin (2014) have examined the volatility of Dhaka Stock Exchange (DSE) using the daily and monthly average DSE General Index (DGEN) between January 1, 2002 and July 31, 2013. This study applies GARCH (1, 1) models to estimate the presence of volatility and found the evidence that volatility is present but decreases over time during the sample period and the highest volatility is observed in 2010 which also support the vulnerability condition of the stock market n 2010.

Siddikee & Begum (2016) have examined the volatility of Dhaka Stock Exchange General Index (DGEN) by applying GARCH (1, 1) process during the period from 2002 to 2013. The findings of GARCH (1, 1) process revealed a huge volatility episode from 2009 to 2012. The author also applied ARCH (m) model in 2004 and 2013 for measuring volatility. The result of the ARCH (m) model confirm reliable estimates of market volatility, 1.10% and 1.46% respectively. The author also conclude that tolerable market volatility have been observed from 2002 to 2009.

This review of literature reveals the fact that measuring the volatility cluster for the frontier market like Dhaka Stock Exchange (DSE) is not commonly observed. Therefore, this study tends to fill this gap by estimating volatility in different stock indexes in DSE.

5. Methodology of the Study

This study is intended to capture the volatility clusters as well as modeling of these volatility in returns of three different stock indices (i.e. DS 30 returns, DSEX returns, and DSES returns) through an econometric application of GARCH (1,1) model. Initially daily stock market indexes has been obtained from January 28, 2013 to November 30, 2016 for DS 30 index as well as DSEX index (i.e. total 839 observation for each index data). But for DSES index daily stock index data from January 20, 2014 to November 30, 2016 (i.e. total 610 index data) has been considered. All the three different index data have been examined for stationarity and if they found to be non-stationary, they will then transformed in to stationary by calculating first difference of log returns. In this case, ADF break point unit root test has been used which can capture the any structural breaks in the data set. If any structural breaks are found then the initial data set will be adjusted by removing the presence of structural breaks. After then, first order autoregressive term will be added in the formation of GARCH (1, 1) regression equation. After estimating the ARCH and GARCH coefficients, then GARCH (1, 1) model has been examined in three different diagnostic (i.e. correlogram Q Statistics, correlogram squared residuals, and ARCH heteroscedasticity test to examine the statistical significance of ARCH term in the regression model. Finally, the anticipated volatility has been captured through presenting conditional variance and forecast of variance for stock returns mentioned above.

5.1 GARCH (1, 1) Model

Autoregressive conditional heteroskedasticity (ARCH) and its generalization, the generalized autoregressive conditional heteroskedasticity (GARCH) model, have proven to be very useful in finance to model the residual variance when the dependent variable is the return on asset or an exchange rate. A widely observed phenomenon regarding asset returns in financial markets suggests that they exhibit volatility clustering. This refers to the tendency of large changes in asset returns (either positive or negative) to be followed by large changes, and small changes in the asset returns to be followed by small changes. Hence there is a temporal dependence in the asset returns. ARCH and GARCH models can accommodate volatility clustering. Suppose, the following regression equation has been considered:

$$Y_t = \rho Y_{t-1} + X\beta + \epsilon_t$$

We typically treat the variance of $\epsilon_t = \sigma^2$ as a constant. However, we might think to allow the variance of the disturbance term to change over time i.e. the conditional disturbance variance would be σ_t^2. Engle postulated the conditional disturbance variance should be modeled as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_p \epsilon_{t-p}^2 \tag{1}$$

The lagged ϵ^2term are called ARCH terms and we can see why this is an 'autoregressive' or AR process. The equation (1) specifies an ARCH model of order p i.e. ARCH (p) model. The conditional disturbance variances ofϵ_t, conditional on information available t time t-1. These higher order ARCH model are difficult to estimate since they often produce negative estimates of the αs. To solve this problem, researchers have turned to the GARCH model proposed by Bollerslev (1986). Essentially the GARCH model turns the AR process of the ARCH model into an ARIMA process by adding in a moving average process. In the GARCH model, the conditional disturbance variance is now:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_p \epsilon_{t-p}^2 + \gamma_1 \sigma_{t-1}^2 + \gamma_2 \sigma_{t-2}^2 + \cdots + \gamma_q \sigma_{t-q}^2$$

$$= \alpha_0 + \sum_{j=1}^{p} \alpha_j \epsilon_{t-j}^2 + \sum_{k=1}^{q} \gamma_k \sigma_{t-k}^2$$

It is now easy to see that the value of the conditional disturbance variance depends on both the past values of the shocks and on the past values of itself. The simplest GARCH model is the GARCH (1, 1) model i.e.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 \sigma_{t-1}^2$$

Thus, the current variance can be seen to depend on all previous squared disturbances; however the effect of these disturbances declines exponentially over time. As in the ARCH model, we need to impose some parameter restrictions to ensure that the series is variance-stationary: in the GARCH (1, 1) case, we require $\alpha_0 > 0, \alpha_1, \gamma_1 \geq 0, and\ \alpha_1 + \gamma_1 < 1$.

6. Analysis and Discussion

This study intends to capture the presence of volatility in three different stock indices (i.e. DS 30; DSEX; and DSES) at Dhaka Stock Exchange. It also attempts to forecast the volatility of the same return data. Initially 817 daily data (from January 28, 2013 to 30 November, 2016) for DS 30& DSEX, and 587 daily data (from January 20, 2014 to 30 November, 2016) for DSES have been considered for unit root test. Table: 2 presents the results of Augmented Dickey-Fuller break-point unit root test for all the three indexes of Dhaka Stock Exchange (DSE). Under null hypothesis this test assumes that the variable under consideration has unit root. The initial ADF break-point unit root test of these index data reveals that these they have unit root which is represented by *p*-values of t-statistics greater than 0.05. To use these data in GARCH (1, 1) test unit root have been removed by measuring return of these index data in the following way:

Return = First difference of log index value * 100

Table 2: ADF Break-Point Unit Root Test

Variables	**t-Statistics**	***p*-value**
DS 30 Index	-3.596462	0.3327
DS 30 Returns	-27.84309	< 0.01
DSEX Index	-3.976276	0.1639
DSEX Returns	-27.11898	< 0.01
DSES Index	-3.901739	0.1928
DSES Returns	-21.04570	< 0.01

Note: Author's own calculations

After measuring return based on the above, these return data have been used to test for the present of unit root one more time. Table: 2 also presents the ADF break-point unit root test of return data series and found that the presence of unit root have been removed. Here the *p*-values of return data are found to be less than 0.05 which implies no unit root in the return data set. Then three different regression equation have been developed for three different return series based on GARCH (1, 1) specification which is presented below:

Mean Equation = Constant + Coefficient * First Order Autoregressive term

Variance Equation = Constant + Coefficient * ARCH term + Coefficient * GARCH term

Table 3: GARCH (1, 1) Equation for DS 30 Returns

Mean Equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003010	0.031525	0.095491	0.9239
AR(1)	0.148003	0.041622	3.555863	0.0004
Variance Equation				
C	0.010398	0.003217	3.232498	0.0012
RESID(-1)^2	0.117739	0.024950	4.718966	0.0000
GARCH(-1)	0.867682	0.022959	37.79328	0.0000

Note: Author's Own Calculation

Table: 3 reveals the GARCH (1, 1) regression estimates of DS 30 return. Here the coefficient of RESID (-1)^2 (which is the ARCH term) is 0.117739 which implies that volatility is affected by previous day's squared residuals. Its coefficient is found to be significant as the *p*-value is less than 0.05. It means that the ARCH coeeficient is significant in explaining the volatility of DS 30 return during the period under consideration. The coefficient of the ARCH term is found to be small which implies lesser volatility in the data set. In the same table, the coefficient of GARCH (-1) indicates the GARCH term (i.e. 0.867682) which implies that conditional variance is affected by previous day's variance. And GARCH coefficient is found to be large and significant for DS 30 return which depicts that there is higher persistence volatility in the data set. That means it will take long time for having any change in the volatility.

Table 4: GARCH (1, 1) Equation for DSEX Returns

Mean Equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.025399	0.025808	0.984157	0.3250
AR(1)	0.145894	0.039510	3.692588	0.0002
Variance Equation				
C	0.004841	0.002926	1.654642	0.0980
RESID(-1)^2	0.130438	0.023175	5.628405	0.0000
GARCH(-1)	0.867166	0.019776	43.84946	0.0000

Note: Author's Own Calculation

Table 4: reveals the GARCH (1, 1) regression estimates of DSEX return. It is found that both the ARCH and GARCH term are statistically significant having *p*-values lesser than 0.05. But the ARCH coefficient of DSEX return (i.e. 0.130438) is

a bit higher than ARCH coefficient of DS 30returns (i.e. 0.117739) which implies that there is comparatively higher volatility for DSEX return than DS 30 return. On the other hand the GARCH coefficient (i.e. 0.867166) for DSEX return is smaller meaning that there is comparatively lesser persistence in the volatility of DSEX return. DSEX return takes lesser time for having any change in the volatility.

In the same way Table: 5 presents GARCH (1, 1) regression estimates of DSES return. It has been found that both the ARCH and GARCH coefficients are statistically significant. Here ARCH coefficient is the lowest one which means least volatility among the selected alternative. On the other hand, GARCH coefficient is found to be the highest with implies longest persistence in the volatility in the DSES returns.

Table 5: GARCH (1, 1) Equation for DSES Returns

Mean Equation				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.005968	0.030917	-0.193034	0.8469
AR(1)	0.165066	0.051911	3.179777	0.0015
Variance Equation				
C	0.003580	0.002451	1.460498	0.1442
RESID(-1)^2	0.097206	0.027803	3.496279	0.0005
GARCH(-1)	0.892703	0.025754	34.66306	0.0000

Note: Author's Own Calculation

Appendix Table 1 reveals the estimates of correlogram Q-statististics with their *p*-values for three different returns series (i.e. DS 30 returns, DSEX returns, and DSES returns). This results have been calculated up to 36 lags with the null hypothesis that there is no serial correlation in the residuals or error terms of the return series. For DS 30 returns, all the *p*-values of the Q-stat are more than 0.05 except at lag 5, 6, and 18. For DSEX return, all *p*-values of the Q-stat are more than 0.05 except at lag 5, 6, 7, 8, 11, 12, 17, 18 and 19. On the other hand, for DSES return, all *p*-values of the Q-stat are more than 0.05 which denotes that the presence of serial correlation has not been found at any lags. Based on this result, it can be said that the mean equation has been correctly specified.

Appendix Table: 2 presents the estimates of correlogram squared residuals for the three alternatives return series. This results reveals that whether the squared residuals are based on the first order autoregressive process or not. It is found that all the p-values are greater than 0.05 i.e. all these estimates fails to reject the null hypothesis of no serial correlation in the residuals up to 36 lags. Based on this observation, it can be said that the squared residuals follows the first order autoregressive process. This evidence implies that the presence of serial correlation has been perfectly removed from the data series.

Finally, Table: 6 presents the statistical significance of ARCH terms in three different return series. Under null hypothesis the ARCH test assumes no ARCH effect in the data set. It is revealed that there is no statistically significant ARCH effect in either one of the three return series. Here the *p*-values of both the F-statistics and Obs*R-squared are found to be more than 0.05 which means that the null hypothesis of no ARCH effect cannot be rejected at 5 percent significant level. Therefore, it can be said that the presence of statistically significant volatility have not been observed in any of the three different return series during the sample period under consideration.

Table 6: ARCH Heteroskedasticity Test

DS 30 Returns	F-statistic	1.279462	Prob. F(1,813)	0.2584
	Obs*R-squared	1.280776	Prob. Chi-Square(1)	0.2578
DSEX Returns	F-statistic	0.606446	Prob. F(1,812)	0.4364
	Obs*R-squared	0.607539	Prob. Chi-Square(1)	0.4357
DSES Returns	F-statistic	0.220791	Prob. F(1,583)	0.6387
	Obs*R-squared	0.221754	Prob. Chi-Square(1)	0.6377

Note: Author's Own Calculation

In appendix, figure: 1, figure: 2, and figure: 3 present the conditional variance of DS 30, DSEX and DSES returns. These figures clearly visualize that the conditional variance of the three different returns have less spikes during the study period especially in case of DS 30 returns. The evidence of less sharp spikes is an indicative of less or no volatility in the return series. On the other hand, forecast of variance for the three different returns have presented in figure: 4, figure: 5, and figure: 6 respectively. All these forecast of variance implies that volatility in all these return series have gradually declines during the sample period. This declining variance forecasts also provide sufficient proof that volatility in these return series gradually reduced which makes statistically insignificant evidence of volatility in the return series. Basically, every stock market is most likely to experience volatility of certain level. Because volatility in one hand is caused by frequent shocks from price sensitive information and one the other caused by noise trading and market rumors. Rational investor would find it worthy to measure the effect of volatility and take advantage of it through forecasting volatility. Dhaka Stock Exchange (DSE) is struggling hard to bring back the confidence of investors for investing in stocks. Regardless of implementing different policy measures, DSE introduced two new indices at the beginning of 2013 and one new index at the beginning of 2014. But all these effort does not found to be effective for bringing confidence of the investors. This lack of market participation from the part of the investors actually lead to have less volatile market performance. Investors have little care about market information which is truly reflected from significant reduction of trading volume in the market place. There are very few investors to trades regularly in the exchange but their effectsare very scanty to reflect in the aggregate market trading volume. If DSE authority initiates few effective measures to motivate investors for trading, then the market performance will come back with its optimal capacity.

7. Conclusion

Measuring and forecasting stock price volatility is one of many basic demands from a diverse group of stakeholders. An informed investor in the market can take a profitable position as well as can develop trading strategies to ensure price benefit. This paper is an attempt to measure the statistically significant presence of volatility in different stock indices at DSE. GARCH (1, 1) model is considered appropriate to identify and measure the volatility that provide less significant evidence of volatility during the sample period. Several diagnostic tests have also been applied to justify the evidence of this study. Finally, volatility forecast provides a gradual reduction of heteroscedasticity in all of the selected stock returns. This empirical evidence reveals that these statistically insignificant volatility coefficients may due to lack of interest from the part of the investors to trade securities in Dhaka Stock Exchange (DSE). On the other hand, volatility forecast indicates the chance of reducing the index values on an average in Dhaka Stock Exchange (DSE) Limited. Furthermore, these findings also call for in-depth analysis and research on same relevant area by employing large sample data and other relevant measures of volatility.

References

Ahmed, M. F. (1998). Equity Market Performance in Bangladesh: An Evaluation. Savings and Development, No. 1, XXII, 67-93.

Ahmed, M. F. (2000).Emerging Stock Market and the Economy. South East Asian Studies Series, Nagasaki University, Japan.

Ahmed, M. F. (2002).Market Efficiency in Emerging Stock Markets: The Case of Dhaka Stock Exchange. Savings and Development, No. 1, XXVI, 49-68.

Aziz. S. I. and Uddin. M. N. (2014). Volatility Estimation in the Dhaka Stock Exchange (DSE). Asian Business Review, 4(1), 41-49.

Banerjee. A. E. & Sarkar. S.(2006). Modeling Daily Volatility of the Indian Stock Market Using Intra-day Data. IIM Calcutta, Working Paper Series No.508.

Batra. A. (2004). Stock Return Volatility Patterns in India. Indian Council for Research on International Economic Relations, Working Paper No. 124.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. Journal ofEconometrics, 31(3), 7-327.

Brooks Chris. (2002). Introductory Econometrics for Finance. (3rd ed.), Cambridge University Press.

Campbell J. Y., Andrew W Lo., and A. Craig MacKinley. (2006). The Econometrics of Financial Markets. (1st Indian ed) New Age International(p) Limited Publications.

Chand. S, Kamal. S, Ali. I. (2012).Modeling and Volatility Analysis of Share Prices Using ARCH and GARCH Models, World Applied Sciences Journal, 19(1), 77-82.

Engle, R.F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica,50 (4), 987-1007.

Engle, R.F. and Bollerslev, T. (1986). Modeling the Persistence of Conditional Variances. Econometric Reviews, 5, 1-50.

Engle, R.F. (2001). The Use of ARCH/GARCH Models in Applied Econometrics. Journal of Economic Perspective, 15 (4), 157-168.

Engle, R.F. and Patton A.J. (2001). What good is a Volatility Model. Quatitative Finance, 1, 237-245.

Glosten, L. R., Jagannathan. R., and Runkle, D. E. (1993). On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stock. Journal of Finance. 48. 1749-1778.

Goudarzi, H. (2010). Modeling and Estimation of Volatility in the Indian Stock Market. International Journal of Business and Management, 5 (2), 85-98.

Kumar S.S.S. (2006). Comparative Performance of Volatility Forecasting Models in Indian Markets. Decisions, 33 (2), 26-40.

Mishra. B, & Rahman. M. (2010). Dynamics of Stock Market Return Volatility: Evidence from the Daily Data from India and Japan, International Business and Economic Research Journal, 9 (5), 79-84.

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. Econometrica, 59, 347-370.

Poon. S-H and Granger. C.W.J. (2003). Forecasting Volatility in Financial Markets: A Review. Journal of Economic Literature, 41 (2), 478-539.

Rahman. M. T. & Moazzem K.G. (2011). Capital Market of Bangladesh: Volatility in the Dhaka Stock Exchange (DSE) and the role of Regulators. International Journal of Business and Management, 6 (7), 86-93.

Siddikee M. N. & Begum N. N. (2016). Volatility of Dhaka Stock Exchange. International Journal of Economics and Finance, 8 (5), 220-229.

Appendix

Table 1: Correlogram Q-Statistics for DSE 30 Returns, DSEX Returns, and DSES Returns

Lags	DS 30 Returns		DSEX Returns		DSES Returns	
	Q-Stat	Prob.	Q-Stat	Prob.	Q-Stat	Prob.
1	0.4320		0.3834		0.1680	
2	0.8153	0.367	1.3855	0.239	0.2422	0.623
3	2.2012	0.333	5.4443	0.066	0.6531	0.721
4	4.2118	0.239	6.9611	0.073	0.6729	0.880
5	11.806	0.019	14.527	0.006	2.5854	0.629
6	11.808	0.038	14.579	0.012	2.6120	0.760
7	11.809	0.066	14.727	0.022	4.0053	0.676
8	11.984	0.101	14.835	0.038	4.0501	0.774
9	11.996	0.151	14.951	0.060	6.3304	0.610
10	12.024	0.212	20.085	0.017	6.3794	0.701
11	12.532	0.251	20.095	0.028	6.8373	0.741
12	12.719	0.312	20.310	0.041	7.4546	0.761
13	12.745	0.388	20.317	0.061	7.7079	0.808
14	12.780	0.465	20.655	0.080	7.7079	0.862
15	13.214	0.510	22.476	0.069	10.849	0.698
16	17.010	0.318	23.254	0.079	22.419	0.097
17	27.680	0.035	28.267	0.029	23.535	0.100
18	27.779	0.048	28.293	0.042	24.221	0.114
19	28.002	0.062	29.428	0.043	24.574	0.137
20	28.024	0.083	29.730	0.055	24.577	0.175
21	28.593	0.096	30.033	0.069	25.291	0.191
22	28.595	0.124	30.253	0.087	27.850	0.144
23	31.639	0.084	30.254	0.112	31.056	0.095
24	33.049	0.080	30.808	0.128	31.056	0.121
25	33.649	0.091	30.835	0.159	33.047	0.103
26	35.728	0.076	32.287	0.150	33.554	0.118
27	35.962	0.092	32.287	0.184	34.098	0.133
28	36.215	0.111	32.334	0.220	34.098	0.163
29	36.950	0.120	32.860	0.241	34.320	0.191
30	37.226	0.141	32.974	0.279	34.474	0.222
31	37.226	0.171	36.816	0.183	34.557	0.259
32	38.276	0.173	37.187	0.205	34.829	0.291
33	39.647	0.166	38.737	0.192	35.219	0.318
34	39.868	0.191	38.950	0.220	39.054	0.216
35	39.878	0.225	39.016	0.254	39.101	0.251
36	40.688	0.234	39.780	0.266	44.174	0.138

Note: Author's Own Calculation

Table2 : Correlogram Squared Residuals for DS 30 Returns, DSEX Returns and DSES Returns

Lags	DS 30 Returns		DSEX Returns		DSES Returns	
	Q-Stat	Prob.	Q-Stat	Prob.	Q-Stat	Prob.
1	1.2870	0.257	0.6096	0.435	0.2236	0.636
2	2.2861	0.319	1.5356	0.464	1.6387	0.441
3	2.3463	0.504	2.2227	0.527	1.6910	0.639
4	2.3470	0.672	2.2246	0.695	2.5006	0.645
5	4.3623	0.499	6.6496	0.248	3.5990	0.608
6	4.7079	0.582	9.4262	0.151	4.5241	0.606
7	5.4646	0.603	9.9490	0.191	4.7028	0.696
8	5.5654	0.696	9.9906	0.266	4.7296	0.786
9	6.0023	0.740	11.017	0.275	5.0499	0.830
10	6.4808	0.773	12.095	0.279	7.5685	0.671
11	6.5152	0.837	12.358	0.337	7.9943	0.714
12	6.7077	0.876	16.244	0.180	9.5253	0.658
13	8.8183	0.787	20.073	0.093	10.446	0.657
14	9.1496	0.821	20.257	0.122	11.115	0.677
15	9.2564	0.864	20.290	0.161	11.379	0.725
16	10.106	0.861	21.046	0.177	11.538	0.775
17	10.342	0.889	21.170	0.219	12.670	0.758
18	10.344	0.920	21.817	0.240	13.207	0.779
19	10.346	0.944	21.969	0.286	14.241	0.769
20	14.808	0.787	25.876	0.170	16.647	0.676
21	15.502	0.797	27.061	0.169	18.402	0.623
22	15.795	0.826	27.136	0.206	18.475	0.677
23	16.898	0.814	27.633	0.230	18.583	0.725
24	17.077	0.845	27.645	0.275	18.815	0.762
25	18.124	0.837	27.678	0.323	19.062	0.794
26	18.128	0.871	27.687	0.374	19.584	0.811
27	21.728	0.751	28.364	0.392	20.076	0.828
28	21.962	0.783	28.683	0.429	20.575	0.843
29	22.648	0.792	29.155	0.457	21.203	0.852
30	24.993	0.725	29.496	0.492	21.342	0.877
31	25.325	0.753	29.620	0.537	21.665	0.893
32	27.454	0.696	29.637	0.587	22.227	0.901
33	31.115	0.561	33.079	0.463	23.332	0.894
34	31.670	0.582	34.053	0.465	23.396	0.914
35	31.774	0.625	34.347	0.499	23.554	0.930
36	32.874	0.618	38.449	0.359	24.263	0.932

Note: Author’s Own Calculation

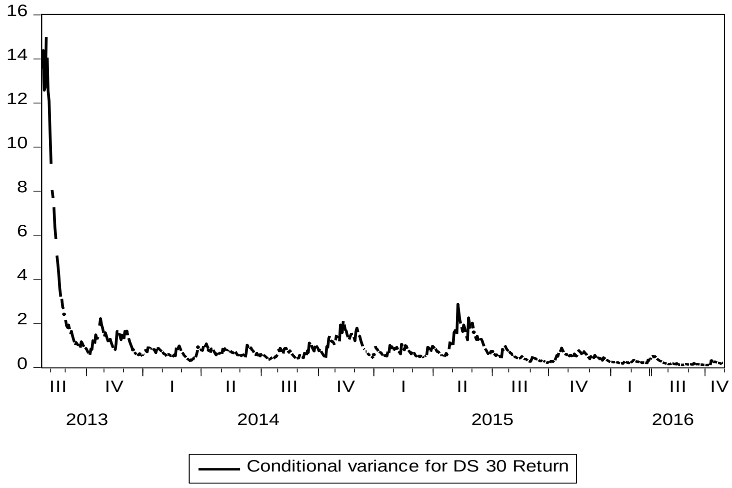

Fig. 1: Conditional Variance for DS 30 Returns

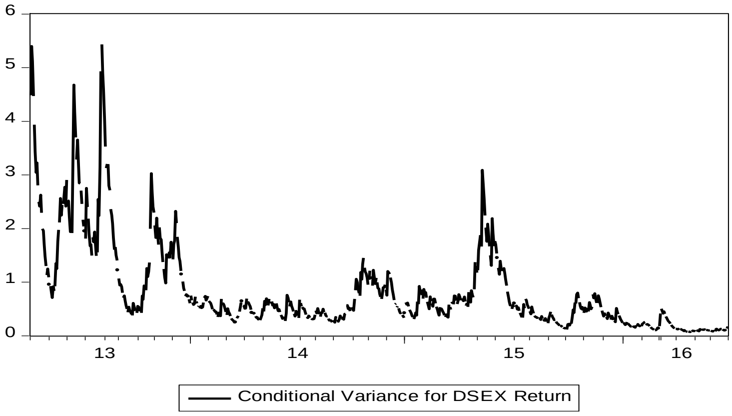

Fig. 2: Conditional Variance for DSEX Return

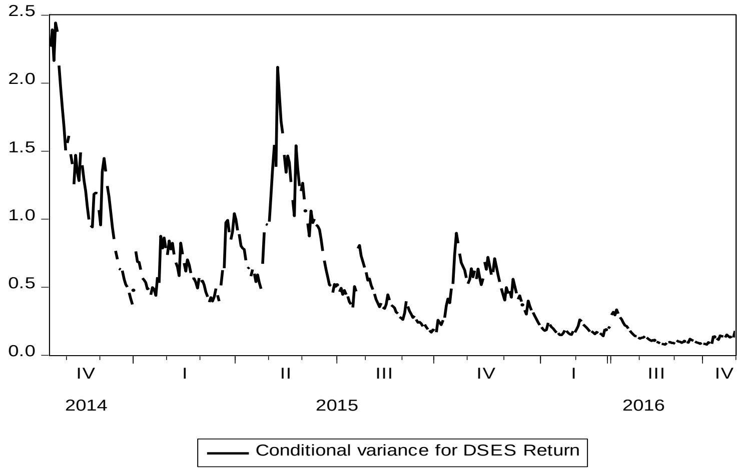

Fig. 3: Conditional Variance for DSES Returns

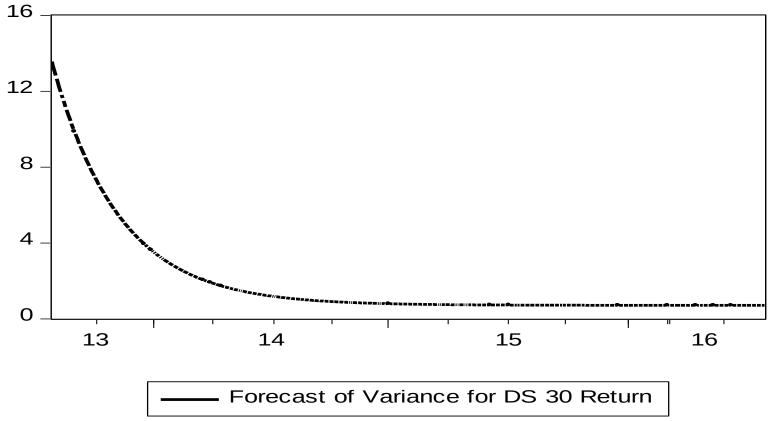

Fig. 4: Forecast of Variance for DS 30 Return

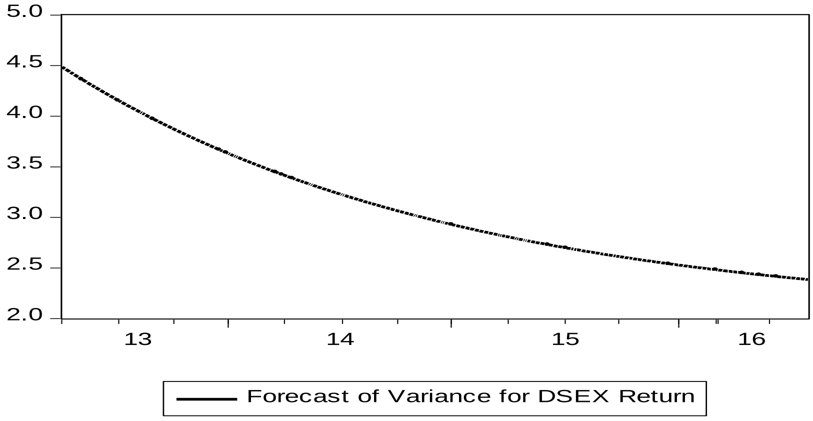

Fig. 5: Forecast of Variance for DSEX Return

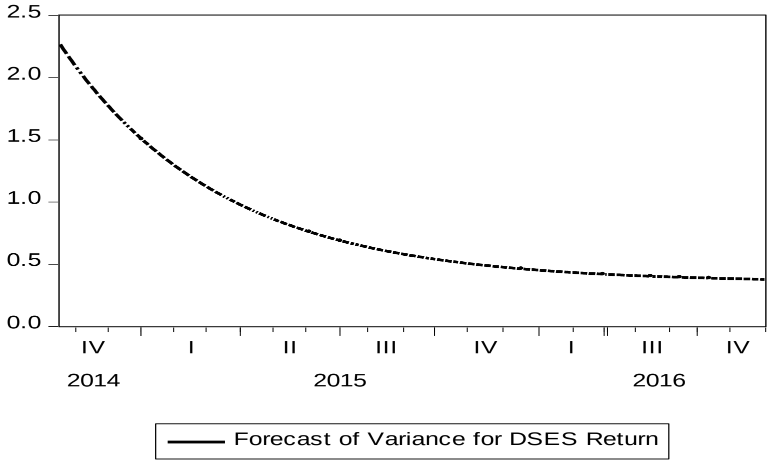

Fig. 6: Forecast of Variance for DSES Returns