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Modeling and Estimating Volatility in the Dhaka Stock Market

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Abstract

Volatility in the stock prices behavior is a normal phenomenon. This is a key element for pricing financial instruments. Financial market volatility also has a wider impact on financial regulation, monetary policy and the macro economy. Study use, daily closing prices data of "DSEX" Broad Index during January 28, 2013 to December 31, 2015. The ARCH and GARCH models are used to estimate the volatility and Phillip Parron test for stationary. Estimated results revealed that the volatility in the Dhaka stock market follow GARCH (1, 1) model i.e. volatility in the Dhaka stock market depends on the past shock in the residual square and the past shock in the variance. Estimated results also revealed its stylized facts volatility clustering, fat tails, persistence of volatility and mean reverting in the series under analysis. The results of the study have useful implications for regulators and policy makers in the Dhaka stock market.

Key Words: Volatility, ARCH, GARCH, Mean Reversion.

JEL Classification: G12, G14

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Introduction

and is a sign of efficiency in stock markets. In an efficient market, stock price fully reflects all available information. Thus, stock price fluctuates in response to new information. The main problem with price fluctuation that affects the financial market efficiency is destructive excess volatility that ends up in crashes and/or crisis in the financial markets. Excessive volatility also reduces the usefulness of stock price as a reflector of the real worth of the firm. After changes in political regime and/or with the inauguration of new government in 1996, the stock market started rising without any connection to company fundamentals. The Dhaka Stock Exchange Index (DSEI) grew from 804 on 31 May 1996 to an all time high of 3596 on 17 November 1996 and then fell to 622.28 on 16 April 1998. Over the passage of time some significant developments took place in Dhaka Stock Exchange (DSE). Our capital market remained buoyant despite collapse of the capital market in many developed and developing countries during global financial crisis in 2007-08. The increasing trend of DSE General Index crossed the 3000 mark in January 2007 and it crossed 8187 points for the first time by the end of 2010. From the beginning of December 2010 market capitalization and share price index decreased gradually and was going to deep correction which continued up to the beginning of 2012 and reached at 3045 points in February 6, 2012. In such a situation, difference between stock intrinsic value and its related market value is significant and has several consequences.

In view of the rapidly increasing role of the stock market, volatility in stock prices can have significant implications on the performance of the financial sector as well as the entire economy. There exists important link between stock market uncertainty and public confidence in the financial market. The policy makers usually rely on the market estimate of volatility as the barometer of the vulnerability of the stock market. Stock return volatility represents the variability of day-to-day stock price changes over a period of time, which is taken as a measure of risk by the relevant agents. High volatility, accompanied by any change in the real situation, may lead to a general erosion of investors' confidence in the market and redirect the flow of capital away from the stock market. Volatility, however, is not an evidence of irrational market behavior or inefficient markets. Stock return volatility is usually asymmetric in its response to past negative price shocks compared with the positive shocks, but what factors drive volatility over time is not clear. Moreover, increase in firm-specific risk appears to adversely affect its stock valuation.

Hence, the study of financial asset volatility is important to academics, policymakers, and financial markets participants for several reasons. First, prediction of financial market volatility is important to economic agents because it represents a measure of risk exposure in their investments. Second, a volatile stock market is a serious concern for policy makers because instability of the stock creates uncertainty and thus adversely affects growth prospects. Evidence shows that when markets are perceived as highly volatile it may act as a potential barrier to investing. Third, the stock market volatility causes reduction in consumer spending. Fourth, pricing of derivative, securities and pricing of call option is a function of volatility. Consequently, it can be seen that the study of stock market volatility and its characteristics is very important and can be helpful for formulation of economic policies and forming rules and regulations related to stock market.

An attempt has been taken in this paper to model and estimate volatility in the Dhaka Stock Exchange. We followed the model used in the paper titled Modeling and Estimation of Volatility in the Indian Stock market by Hojatallah Goudarze. The remainder of the paper is organized as follows: section 2 describes the volatility model; literature review is presented in section 3; methodology is analyzed in section 4; findings are explained in section 5; and finally concluding remarks is in section 6.

2. Models of volatility:

In modeling and capturing many of the stylized facts of the volatility behavior usually observed in financial time series including time varying volatility or volatility clustering *(Zivot and Wang, 2006)* ARCH models are being used widely.

The serial correlation in squared returns, or conditional heteroskedasticity (volatility clustering), can be modeled using a simple autoregressive (AR) process for squared residuals. For example, let y_t denote a stationary time series such as financial returns, then y_t can be expressed as its mean plus a white noise if there is no significant autocorrelation in y_t itself:

$$Y_t = c + \varepsilon_t \quad (1)$$

Where c is the mean of y_t and ε_t is iid with mean zero. To allow for volatility clustering or conditional heretoskedasticity, assume that $Var_{t-1}(\varepsilon^2) = \sigma_t^2$ with $var_{t-1}(.)$ denoting the variance conditional on information at time t-1, and

$$\sigma^2_t = \alpha_0 + \alpha_1 \alpha_1 \varepsilon^2_{t-1} + \ldots\ldots + \alpha_p \varepsilon^2_{t-p} \quad (2)$$

Since ε_t has zero mean, $Var_{t-1}(\varepsilon^2) = \alpha_t^2$, the above equation can be rewritten as:

$$\varepsilon^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \ldots\ldots + \alpha_p \varepsilon^2_{t-p} + u_t \quad (3)$$

Since an ARCH model can be written as an AR model in terms of squared residuals as in equation 3, A simple Lagrange Multiplier (LM) test for ARCH effects can be constructed based on the auxiliary regression as in equation 3.

Under the null hypothesis that there is no ARCH effects:

$$H_0=\alpha_1=\alpha_2= \ldots\ldots\alpha_p=0$$

the test statistics is $LM=T.R^2 \sim x^2(p)$

Where T is the sample size and R^2 is computed from the regression (3) using estimated residuals. If P-value is smaller than the conventional 5% level, the null hypothesis that there are no ARCH effects will rejected. In other word, the series under investigation shows volatility clustering or persistence. If the LM test for ARCH effects is significant for a time series, one could proceed to estimate an ARCH model and obtain estimates of the time varying volatility σ^2 based on the past history. A more parsimonious model proposed by Bollerslev (1986) replaces the AR model in (equation 2) with the following formulation:

$$\sigma^2=\alpha_0+\sum_{i=1}^{p}\varepsilon^2_{t-i}+\sum_{i=1}^{p}b_j\sigma^2_{t-j} \qquad (4)$$

The model in (equation 4) together with (equation 1) is known as the generalized ARCH or GARCH (p, q) model. When q=0, the GARCH model reduces to the ARCH model.

Under the GARCH (p, q) model, the conditional variance of $\varepsilon_t, \alpha^2 t$, depends on the squared residuals in the previous p periods, and the conditional variance in the previous q periods. Usually a GARCH (1, 1) model with only three parameters in the conditional variance equation is adequate to obtain a good model fit for financial time series (Zivot and Wang, 2006).

2.1 ARCH effect test process

Consider the k-variable linear regression model.

$$Y_t = \beta_1 + \beta_2 X_{2t} + \ldots\ldots\ldots\ldots\ldots\ldots + \beta_k X_{kt} + u_t$$

In addition, assume that conditional on the information available at time (t-1), the disturbance term distributed as

$$u_t \sim [0,(\alpha_0+\alpha_1 u^2_{t-1})]$$

That is, u_t is normally distributed with zero mean and

$$Var(u_t) = (\alpha_0 + \alpha_1 u_{t-1}^2)$$

That is the variance of u_t follows an ARCH(1) process. The variance of u at time t is dependent on the squared disturbance at time (t-1), thus giving the appearance of serial correlation. The error variance may depend not only on one lagged term of the squared error term but also on several lagged squared terms as follows:

$$Var(u_t) = \sigma^2_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots\ldots + \alpha_p u_{t-p}^2$$

The null hypothesis can be tested by the usual F test but the ARCH-LM test of Engle (1982) is a common test in this regard. Under ARCH-LM test the null and alternative hypothesis for DSEX broad stock index are as follows:

$$H_0: \alpha_1 = 0 \text{ and } \alpha_2 = 0 \text{ and } \alpha_3 = 0 \text{ and } \ldots\ldots\alpha_q = 0$$

$$H_1: \alpha_1 \neq 0 \text{ and } \alpha_2 \neq 0 \text{ and } \alpha_3 \neq 0 \text{ and } \ldots\ldots\alpha_q \neq 0$$

Null hypothesis in this case is homoskedasticity or equality in the variance. Acceptance of this hypothesis imply that, there is no ARCH effects in the under process series. In other word, the data do not show volatility clustering i.e. there is no heteroskadasticity or time varying variance in the data.

If an ARCH effect is found to be significant, then the specification of an appropriate ARCH model is necessary. In order to identify the ARCH characteristics in DSEX, the conditional return should be modeled first; the general form of the return can be expressed as a process of autoregressive AR(p), up to (p) lags, as follows:

$$R_t = \alpha_0 + \Sigma_{i=1}^{q} \beta_1 R_{t-1} + \varepsilon_t$$

This general form implies that the current return depends not only on (R_{t-1}) but also on the previous (p) return value (R_{t-p}).

The next step is to construct a series of squared residuals (ε^2_t) based on conditional return to drive the conditional variance. Unlike the OLS assumption of a constant variance ($\varepsilon_{t,}$s), ARCH models assumes that ($\varepsilon_{t,}$s) have a non constant variance or heteroscedasticity, denoted by (h_t^2) . After constructing time series residuals, we have modeled the conditional variance in a way that incorporates the ARCH process of (ε^2) in the conditional variance with (q) lags .

The general forms of the conditional variance, including (q) lag of the residuals is as follows:

$$h_t^2 = \beta_0 + \Sigma_{i=1}^{q} \beta_1 \varepsilon^2_{t-1}$$

The above equation is what Engle (1982) referred to as the linear ARCH (q) model because of the inclusion the (q) lags of the (ε^2) in the variance equation. This model suggests that volatility in the current period is related to volatility in the past periods.

To determine the value of q or the ARCH model order, we use the model selection criterion such as AIC (Akaike Information Criterion) and SBIC (Schwartz Bayesian Information Criterion). The decision rule is to select the model with the minimum value of information criterion. This condition is necessary but not enough because the estimate meets the general requirements of an ARCH model. The model to be adequate should have coefficient that all are significant. If this requirement meets then the specified model is adequate and fit the data well.

2.2 Mean Reversion

The high or low persistence in volatility is generally captured in the GRACH coefficient(s) of a stationary GARCH model, for a stationary, GARCH model the volatility mean reverts to its long run level, at rate given by the sum of ARCH and GARCH coefficients which is generally close to one for a financial time series.

3. Literature Review

Volatility in the stock prices behavior is a normal phenomenon but what causes stock prices volatility is a question that remains unsettled in the finance field. After introducing ARCH model by Engle (1982) many studies accomplished in developed country and to some extent in developing country. Of these a few studies has been reviewed here.

Kim and Singal (1993) suggested that there were no increase in volatility over time, and that volatility tended to decrease following market liberalization. Engle and Ng (1993), estimated the impact of bad and good news on volatility. Market volatility is assumed to be associated with the arrival of news. They found an asymmetry in stock market volatility for bad news as compared to good news Bad news is associated with sudden drop in price while good news is associated with sudden rise in price. They found that bad news create more volatility than good news of equal importance. This asymmetric characteristic of market volatility has come to be known as the “leverage effect”. Engle and Ng (1993) provided new diagnostic tests and models, which incorporate the asymmetry between the type of news and volatility. Fouque et al (1999), presented a derivative pricing and estimation methodology for a class of stochastic volatility models that exploits the observed persistent nature of stock price volatility. Empirical analysis of high frequency S & P 500 index data for European option prices confirms that volatility reverts slowly to its mean in comparison to tick-by-tick fluctuations of the index value, but it is fast mean reverting when looked at over the time scale of a derivative contract. Batra, A. (2004) examined the time variation in volatility in the Indian stock market during 1979-2003. Using monthly data and asymmetric GARCH methodology augmented by structural change analysis, the paper revealed that the period around the BOP crisis and the subsequent initiation of economic reforms in India was the most volatile period in the stock market. Stock return volatility in India seems to be influenced more by domestic political and economic events rather than by global events. The analysis in the paper also revealed that stock market cycles in India have not intensified after financial liberalization. A generalized reduction in stock market instability was observed in the post- reform period in India. Banerjee and sarkar (2006), in the article "long memory property of stock return; evidence from India" investigated 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. Goudarzi (2013), using daily data for the period 2000 to 2010 showed that Indian stock market are characterized by mean reversion and inconsistent with the efficient market hypothesis. This evidence shows that Indian stock market to be informationally weak-inefficient. He suggested that to improve the efficiency of the market and secure the flow of information to the market participants, the policy makers must take this into account to prevent any speculation which may affect the intrinsic value of the share and cause crashes and/or crises.

There are few studies on the volatility of Dhaka stock exchange. Some of the studies are reviewed here. Haque et al (1998), examined whether the introduction of automated trading along with the changes in regulatory measures changed the risk return composition and thus improved the market efficiency of the DSE. They concluded that the DSE at best can be considered as weak-form efficient and the automation and other regulatory measures have done little or nothing at all to change the risk return composition of the market. Within the GARCH type framework Basher et al. (2007) investigated the time varying risk-return relationship and the impact of institutional factor on the volatility of stock return in Bangladesh using daily and weekly DSE stock return. Capital market in Bangladesh has gone through a structural change in 1990s when foreign investors were allowed to invest in the capital market. The DSE returns showed negative skewness, excess Kurtosis and deviation from normality. In addition to this, the DSE returns exhibited serial correlation indicating stock market inefficiency. They found a significant relationship between conditional volatility and DSE stock return. They also found that lock-in has no significant impact on stock volatility, while, circuit breaker has some influences on the volatility of daily and weekly stock return for both pre-and post-liberalization samples. They suggested that in order to improve the operation of the capital market the government should emphasis a policy of timely disclosing and disseminating the information to the investors and stakeholders on the performance of listed companies. Imam and Amin (2004) found that volatility in the return of capital market in Bangladesh follows a generalized autoregressive conditional heteroskedastic (GARCH) process. It has been observed that the volatility predicted this period has more influence in forecasting volatility for the next period. Dhaka Stock Market today's return has a large effect on the conditional forecast variance many periods in the future, indicating, for the DSE return series, volatility clustering is said to be persistent. The GARCH model exhibits different results for two sub-periods of pre-crash and post- crash period. High volatility in the later period as well as the change in the behavior of investors after the stock market crash in 1996 are the reasons for the structural shift in the GARCH process. Lack of confidence by the long term individual investors, passive role run by institutional investors, and the dominance of speculators are the major reasons for the change in investor's behavior. They found that conditional volatility of DSE index in post-crash period is mean reverting. This finding suggests that current information has no effect on long run forecasts and volatility shocks (random error) influences more in estimating future volatility than the volatility estimated at earlier period. Rahman and Hossain (2007) examined the stock price volatility in the Dhaka stock Exchange (DSE) for the period of 2003-2007. They showed that Dhaka stock Exchange market experiences excessive volatility in this period that comes from both the supply side and demand side factor, while supply side variables (issued capital) fluctuates less than demand side variables, market capital. They found that demand side pressure (upward price adjustment) had contributed to the volatility of stock of index during the year of 2003, 2004 and 2007, while excess sharp fall in price index in the year of 2005 and 2006 had come from excess supply of shares. They recommended that active participation of the government through issuing supply of stocks can help to mitigate the excessive volatility in the capital market. However, identifying the factors behind price movement and disseminating the information to the investors are necessary to handle the situation during the unpredicted price movement period. Using monthly DSE General Index for the period of January 1987 to March 2010 Rayhan et al. (2011) found that monthly DSE return follow Generalized Autoregressive Conditional Heteroskedasticity (GARCH) properties. Islam et al. (2012) examined the relative ability of various models to find out the best forecasting model for

Bangladesh. They found that linear models dominate over non-linear models for forecasting stock index future volatility and they suggested that moving average model appears to be the best in this regard. This study is different from other studies as unlike other studies, this study use daily 'DSEX' broad index for the period 2013 to 2015. And also has made an attempt for modeling and estimating volatility in the Dhaka stock market.

4. Methodology

The DSE Broad Index ("DSEX") with effect from January 28, 2013 which reflects around 97 percent of the total market capitalization has been used in the study. Daily closing prices data of "DSEX" Broad Index during January 28, 2013 to December 31, 2015 is obtained from Dhaka Stock Exchange. A continuous sequence of 764 observations of closing price data is gathered over the last three years period. The logarithm of price relatives of DSEX indices (p), is used to calculate the price changes of DSEX returns (r). That is at time t the daily DSEX return is $r_t = \log(P_t/P_{t-1})$. Visual inspection of the plot of residual of daily return series of DSEX indices shows that return fluctuates around mean value that is close to zero (chart 2). The ARCH and GARCH models are estimated for DSEX return series assuming the student t – distribution. We use information criteria such as AIC and SBC values, and model diagnostic tests (ARCH-LM test and Q-Statistics) to choose the volatility model which represents the conditional variance of the DSEX broad index series appropriately. We estimate the model using Eviews 9.

5. Results and discussions

The distributional properties of daily DSEX index return are reported in Chart 1. The mean daily return is 0.000162, the volatility (measured as a standard deviation) is 0.009463. There is indication of negative skewness (-0.131) , which indicates that the lower tail of the distribution is ticker than the upper tail, that is, the index declines occur more often than its increases. The kurtosis coefficient (5.759) is positive, having high value for the return series, that is, the pointer of leptokurtosis or fat taildness in the underlying distribution. Under the null hypothesis of normality the Jarque- Bera statistics asymptotically follows a Qi-square distribution. The computed value of 244.09 with P-value of zero rejects the normality assumption due to the high kurtosis indicating fat tail. The chart 2 shows volatility clustering where large returns tend to be followed by small returns leading to continuous periods of volatility and stability. Volatility is high for certain time periods and low for other periods. The movements are in the positive and negative territory and large fluctuations tend to cluster together separated by periods of relative calm. The volatility was highest throughout the year 2013 and second quarter of 2015. Q-Q plot in chart 3 also confirm the non-normality of the return series.

To detect the presence of ARCH effect in the mean equation of DSEX broad index we use ARCH-LM (Lagrange Multiplier) test. We tested for ARCH effect for higher order and found that coefficient of $\varepsilon^2_{t-4,}\varepsilon^2_{t-6,}\varepsilon^2_{t-7,}$ and ε^2_{t-9} are statistically insignificant. ARCH-LM test is statistically significant which indicates the presence of ARCH effect in the residuals of mean equation of DSEX broad index (Table-1). To determine which ARCH model is adequate for describing the conditional heteroskedasticity of the data we apply sample ACF and PACF of the squared residuals which showed the existence of ARCH effects. The PACF indicated that an ARCH (3) model might be appropriate . Consequently, we specify the ARCH (3)model as follows:

$$r_1 = \mu + \alpha_1 \, r_{t-1} + \varepsilon_t$$

$$\sigma^2 = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \varepsilon^2_{t-1} + \alpha_2 \varepsilon^2_{t-2}$$

The result for the ARCH (3) for daily log return of DSEX broad index is reported in (Table-2). As table-2 shows that the estimates of α_1, α_2 and $\alpha 3$ are all statistically significant at the 1% level of significance. Therefore, the model needs not to be simplified. Therefore, we choose ARCH (3) for our data set of DSEX broad index. Using AIC, SBC, Hannan-Quinn model selection criterion we achieved same results.

To test the adequacy of the model we applied the ARCH-LM test up to three lag. The result has reported in the Table-3. As Table-3 indicates, both test statistics are statistically insignificant. It means no ARCH effect left in the model. Thus, we found that ARCH (3) can be possible representation of the conditional volatility process for daily return series of DSEX broad index. Hence, we obtain the following fitted model for mean and variance equations.

$$r_t = 0.00025 + 0.141474 \, r_{t-1} + \varepsilon_t$$

$$\sigma^2 = 3.88\text{E-}05 + 0.149559\, \varepsilon^2_{t-1} + 0.252418\, \varepsilon^2_{t-2} + 0.166072\, \varepsilon^2_{t-3}$$

GARCH Model:

Although the ARCH model is simple, it often requires many parameters to adequately describe the volatility process of an asset returns. Bollerslev (1986) proposes a useful extension known as the generalized ARCH (GARCH) model. The modeling process of ARCH model can also be used to build a GARCH Model. However, specifying the order of GARCH model is difficult. For this reason, only lower order of GARCH models are used in most application. We fit the GARCH models with different orders (up to 5) to the DSEX daily return series. To select the order of GARCH model, we used SBC criteria as

SBC select the parsimonious model. The model with lower value of SBC fits the data best. The results are presented in Table 4. As Table-4 shows, the SBC value is lowest for $p = 1$ and $q = 1$. Therefore, we choose GARCH (1, 1) for our data set of DSEX broad index. Thus we found that GARCH (1, 1) can be possible representation of the conditional volatility process for daily return series of DSEX broad index. Table-5 reports the statistics regarding GARCH (1,1). To test the adequacy of GARCH (1,1) model we apply ARCH-LM test up to 10 lag. The results of ARCH-LM test are reported in Table-6. As results shows the F-Statistics and obs* R squared statistic both are insignificant and indicating no ARCH effect left in the series.

Thus, we employed GARCH (1, 1) to model volatility. The model of volatility for DSEX broad index using GARCH (1, 1) are as follows:

$$r_t = 0.000243+0.131874\, r_{t-1} + \varepsilon_t$$

$$\sigma^2 = 3.09E\text{-}06 + 0.150804\, \varepsilon^2_{t-1} + 0.817553\, \sigma^2_{t-1} + \varepsilon_t$$

As above model indicates the value of á is 0.150804 and the value of β is 0.817553, the sum of parameters (α + β) is 0.97. The stationary condition (α + β<1) is satisfied. The mean reverting rate (α + β) = 0.97, implied by our fitted model is close to one. Therefore, the fitted GARCH model implies that conditional volatility is very persistent. A large value of GARCH lag co-efficient β (0.817553) indicates that shocks to conditional variance takes a long time to die out, so the volatility is persistent. Low value of error coefficient α i.e. (0.150804) suggests that large market surprises induce relatively small revision in future volatility. The sum of α and β is close to unity (α + β = 0.97), a high value of this kind implies a “long memory” in the stock market. The stationary condition of (α + β<1) implies that it is mean reverting and volatility finally revert to its long run average.

6. Conclusions

The study attempted to model and estimate volatility in the Dhaka stock market and its stylized facts. The study used 764 observations of daily closing price of DSEX broad index for the period January, 2013 to December, 2015. The analysis showed that the stock market volatility changes significantly over time. Empirical results showed that the volatility in the Dhaka stock exchange follow GARCH (1, 1) model. That is, volatility in the Dhaka stock market depends on past shock in the residual square and past shock in the variance. Our results revealed that GARCH (1, 1) model adequately describe the DSEX broad index and its stylized facts volatility clustering, fat tails and mean reverting in the series under analysis. The results suggest that the volatility in the Dhaka stock market exhibits the persistence of volatility and mean reverting behavior.

Table - 1. ARCH-LM test of DSEX broad index log returns series to 36 lags

ARCH - LM TEST			
F-statistics	5.359774	Probability	0.0
Obis*R-Squared	158.833	Probability	0.0

Table - 2. ARCH(3) model parameters

ARCH (3) model parameters				
Mean Equation				
	Coefficient	Std.Error	Z-Statistics	Prob.
C	0.00025	0.000297	0.841921	0.3998
AR(1)	0.141474	0.036064	3.922873	0.0000
Variance Equation				
C	3.88E -05	3.55E - 06	10.91455	0.0000
ARCH(1)	0.149559	0.038318	3.903131	0.0001
ARCH(2)	0.252418	0.046878	5.384566	0.0000
ARCH(3)	0.166072	0.05716	2.905382	0.0037

Table - 3. ARCH-LM test for ARCH(3) model upto 3 lag

ARCH (3) TEST			
F-statistics	0.300133	Probability	0.8253
Obis*R -Squared	0.904093	Probability	0.8244

Table - 4. SBIC for different GARCH model

Comparisons of the SBC for the GARCH(p,q) model with different combinations of p and q for DSE Index					
P	1	2	3	4	5
q					
1	-6.674286	-6.669133	-6.660691	-6.652413	-6.644508
2	-6.667529	-6.660531	-6.653509	-6.648673	-6.638282
3	-6.660897	-6.652497	-6.655078	-6.646544	-6.637855
4	-6.657363	-6.653713	-6.646567	-6.637893	-6.62506
5	-6.648875	-6.653386	-6.646339	-6.638053	-6.643303

Table - 5. GARCH (1,1) parameters

GARCH (1,1) Parameters				
Mean Equation				
	Coefficient	Std. Error	Z-Statistics	Prob.
C	0.000243	0.000279	0.870689	0.3839
AR(1)	0.131874	0.039843	3.309825	0.0009
Variance Equation				
C	3.09E -06	1.15E -06	2.67655	0.0074
ARCH(1)	0.150804	0.023346	6.459432	0.0000
GARCH(1)	0.817553	0.029406	27.80227	0.0000

Table - 6. ARCH-LM test for GARCH (1,1) model up to 10 lag

ARCH (10) TEST			
F-statistics	0.818878	Probability	0.6105
Obs*R -Squared	8.219511	Probability	0.6074

Chart -1. Descriptive Statistics of DSEX Daily Return

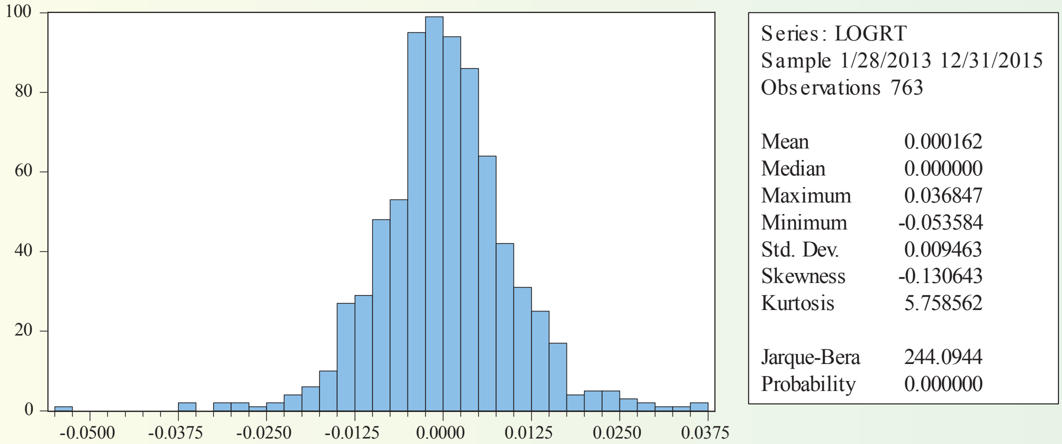


Chart - 2. The Residuals of DSEX Daily Return

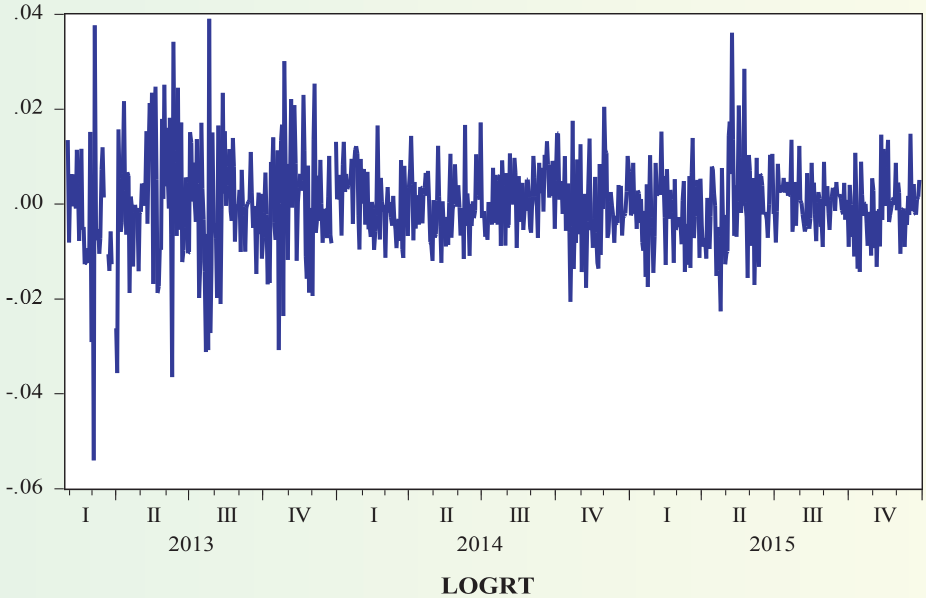
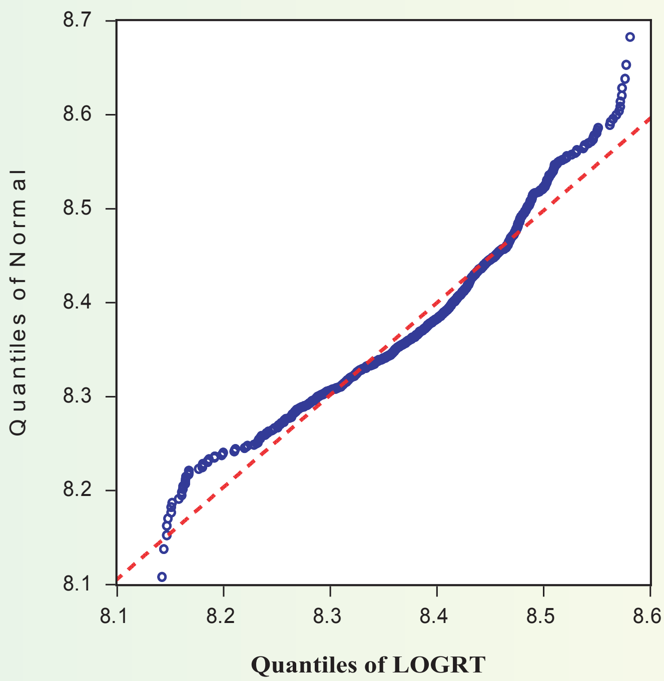


Chart -3. Q-Q plot of DSEX Daily Return Series



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