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Market Efficiency, Time-Varying Volatility and Equity Returns in the Dhaka Stock Exchange

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This paper examines the stock prices in the Dhaka Stock Exchange (DSE) in order to test the efficient market hypothesis in pricing securities and the relationship between stock returns and conditional volatility using best known daily price indices DGEN ranging from January 2004 to April 2013. The findings are that the stocks in DSE follow a random walk which suggests that the market meets the criterion of weak form efficiency. The ARIMA confirms the random walk hypothesis. The results of GARCH (p, q) model indicates the tendency for returns to exhibit volatility clustering; and a significant positive link between risk and returns for DGEN index. Thus, it can be inferred that the mean variance hypothesis holds for DSE as the evidence is found that investors are rewarded for taking increased risk for the securities of DSE. The implications of these results are that the investors cannot earn excess returns in the long run by using the historical share prices as the basis of making investment strategies.

Keyword: Volatility, Market Efficiency, ADF test, ARIMA Model, GARCH (p, q) Model

1. Introduction

The capital market plays a strong role in the industrialization and economic development of a country. Dhaka Stock Exchange (DSE), the leading stock exchange of Bangladesh, is a new and emerging stock exchange located in the capital city of the country. It was first established on April 28, 1954, as the then East Pakistan Stock Exchange Association Ltd. But the formal trading began in 1956 with 196 listed securities with a total paid up capital of about Taka 4 billion. On June 23, 1962, it was renamed “East Pakistan Stock Exchange Ltd.” Again on May 14, 1964, the name was revised as “Dhaka Stock Exchange Limited”. The trading was suspended due to the liberation war in 1971. However, the operation was resumed in 1976 with only 9 listed companies with a paid up capital worth0.138 billion Taka and market capitalization of 0.147 billion Taka, which was 0.138% of GDP. As of September 30, 2010, there were 461 securities listed in the DSE with market capitalization worth 3260.28 billion Taka. The DSE is registered as a Public Limited Company and its operational activities are regulated by its Articles of Association and its own rules, regulations and by-laws along with the Bangladesh Securities and Exchange Ordinance 1969, the Company Act, 1994, and the Securities and Exchange Commission (SEC) Act, 1993. Various policies have been adopted by the SEC and DSE in various times to run the market smoothly.

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Fluctuations in the prices of shares and other assets play an important role in economic dynamics. An organized and well developed capital market is crucial for capital formation, efficient resource allocation, and acceleration of economic growth. It plays an intermediary role between lenders and borrowers to facilitate savings into investments. The DSE has undergone a radical transformation in the past decade. The appropriation of international quality trading and settlement mechanisms and adoption of strategies to reduce transaction costs have made the investors more optimistic which resulted in a considerable growth in market volume and liquidity. The market promoted a developed regulatory framework, a modern market infrastructure, removal of barriers to the international equity investment, better allocation and mobilization of domestic resources and increased market transparency. These reforms contributed to the stages for significant market expansion, with a trend of development in size and liquidity. The market witnessed significant progress in the perspective of new equity issues, volume and value of trading and the number of traded companies. As a result, market capitalization increased from 1.3764 percent to 16.2849 percent of GDP during 1990-2009 and the turnover ratio increased from 1.6843 percent to 54.2524 percent (Hossain & Uddin 2011). Considering all these things we can deduce the better efficiency of Bangladesh's Dhaka Stock market. However, in spite of this transformation the DSE showed greater volatility which has affected the informational efficiency of DSE. It has been experiencing volatility since its inception. The volatility indices reached the highest level in its history in November 1996 and finally crashed which caused the investors to lose their confidence about the stock market. As a result, the automated trading was initiated on August 10, 1998 and started on January 1, 2001. Also, a Central Securities Depository system was initiated on January 24, 2004. As of November 16, 2009, the benchmark index of the DSE exceeded 4000 points for the first time hitting another new high at 4148 points. Again the index crossed 8500 points in 2010 and eventually crashed in the first quarter of 2011. Millions of investors lost their money and came out onto the street blaming the speculators and regulators for the bubble that finally burst in what became known as the 2011 Bangladesh share market scam. The crash is believed to be caused artificially to benefit a handful of players at the expense of the big players.

In the finance literature efficient market hypothesis (EMH) asserts that capital markets are informationally efficient. Companies and investors expect existing share prices to always incorporate and reflect all relevant information so that stocks always trade at their fair values on stock exchanges, making it impossible for investors to consistently achieve returns in excess of average market returns on a risk-adjusted basis. There are three versions of EMH: weak, semi-strong, and strong. The weak form of the EMH claims that current prices of assets (*e.g.,* stocks, bonds, or property) are not predictable from past prices (Fama 1991) and hence follow a random walk. The semi-strong form of efficiency EMH affirms both that current prices reflect all publicly available information and that prices instantly change to reflect new public information. Finally, the market is strong form efficient if additionally prices instantly reflect even hidden or "insider" information.

However, though the EMH is a cornerstone of modern financial theory, it is highly controversial and often disputed. Critics have consistently blamed and beaten the belief in 'rational markets' pointing to the events such as the 1987 stock market crash when the Dow Jones Industrial Average (DJIA) fell by over 20% in a single day (Investopedia) and the financial crisis in late 2000s, as evidence that stock prices can seriously deviate from their fair values. In response, the believers argue that the market efficiency hypothesis does not necessarily imply having no uncertainty about the future, rather the hypothesis is a simplification of the world which may not always hold true and the market is practically efficient for investment purposes for most individuals.

The paper investigates the efficiency and volatility of stock prices and justifies whether the investors can expect future gain from investment into the stock market on the basis of available history of stock prices. All techniques applied for testing efficiency ends up with uniform results in favour of EHM which coincided with some of the past research findings, while the volatility test established a significant positive relationship between risk and returns which partly opposes the findings of previous studies.

The rest of the paper is organized as follows. Section 2 of the paper reviews the literature in connection with the volatility of stock prices. Section 3 describes the source of data. Section 4 illustrates the methodology of the study. Some descriptive statistics for measuring stock returns of DSE are computed in section 5. The results of diagnostic test such as stationarity test, ARIMA, and GARCH are discussed in section 6 and finally section 7 concludes.

2. Literature Review

The efficiency market hypothesis is one of the most controversial and well-studied propositions in the literature of capital market. Summers (1986) found that the power of statistical tests used to evaluate the efficiency of speculative markets were very low. This means, though the efficient markets hypothesis could not be rejected from the evidence; it should not be concluded that market prices represent rational assessments of fundamental valuations. Using a simple volatility-based specification test, Lo and MacKinlay (1988) rejected the random walk hypothesis for weekly stock market returns. Fortune (1991) also found the evidence against the efficient market hypothesis. On the other hand, Pearce (1987) advocated the efficiency of stock market despite some apparent anomalies. The number of studies related with efficiency hypothesis corresponding to the DSE is very few. However, some studies showed evidence of efficiency hypothesis whereas other studies did not. For example, applying runs and autocorrelation tests, Mobarek and Mollah (2002) concluded that the daily price index series of the DSE (for the period 1988 - 1997) did not follow a random walk. Kader and Ataur (2005) used filter rule to test the hypothesis of weak form efficiency and found that the DSE is not efficient in weak form. Hassan, Islam & Basher (2000) and Rahman and Hossain (2006) found similar result.

Furthermore, studies such as, Chowdhury (1994), Hassan and Maroney (2004), Ainul and Khaled (2005), Kader and Rahman (2005), Basher, Hassan & Islam (2007), Uddin and Alam (2007), Mobarek et al. (2008), Uddin and Khoda (2009) also do not support the contention that the DSE exhibit the weak form of efficiency. These findings imply the possibility of earning abnormal profit following a specific trading rule on a regular basis that violets the random walk hypothesis. On the other hand, applying a variance ratio test, Alam, Hasan & Kadapakkam (1999) found that the monthly stock price index series of the DSE during 1986 to 1995 followed a random walk, which implies the weak form efficiency. Islam and Khaled (2005) found evidence in favor of short term predictability of share prices in the DSE prior to the 1996 boom, but not during the post-breakdown period. Hassan and Chowdhury (2008) and Uddin and Shakila (2008) also support the existence of weak form efficiency in the DSE market. However, Cooray and Wickremasinghe (2005) found mixed result for Bangladesh. Their classical unit-root test supports weak form efficiency but DF-GLS and ERS do not.

Besides, to the best of the authors' knowledge, few studies focus on the relationship between risk and return over the past decades in the DSE. Basher, Hassan & Islam (2007) tried to figure that out using the GARCH model. But their findings seem very contradictory. Hassan, Islam & Basher (2000) used GARCH-M to measure the time-varying risk-return relationship and found a significant relationship between conditional volatility (risk) and the stock returns.

However, the risk-return parameter in their study is negative and statistically significant which is not consistent with the portfolio theory.

The disagreement regarding the efficient market hypothesis has generated interest of further research on this topic. It examines if the DSE manifests-the weak form market efficiency. This paper is also an attempt to reinvestigate the strength and direction of the risk-return relationship in the DSE using a new set of data, DGEN.

3. Data Sources

The empirical analysis in this study uses a time series of DSE index collected from DSE website. Also known as DGEN, DSE index is computed from the daily closing prices of stocks enlisted in the DSE. It was introduced in 2001 with a base point of 817.62, listed in the website from June 1, 2004 and finally replaced by a new index named DSEX in January 27, 2013. However, the prime bourse had decided that the DGEN would be continued to be displayed along with the new DSEX on the screen for some months so that people would not get confused. Therefore, the sample period considered in this study spans from June 1, 2004 to April 15, 2013, generating a sample size of 2123 daily observations.

4. Methodology

This paper revisited two testable hypotheses namely (i) the DGEN index is nonstationary, i.e. there is a random walk in the DSE and hence the market is efficient and (ii) the conditional volatility for DSE stock returns is time-invariant. If the market follows a hypothesis of weak-form efficient, the stock prices should be a random walk or stochastic process. This indicates that the successive price changes of DSE are independent and identically distributed (i.i.d.) random variables. If the market is efficient, then the current securities prices are fully and instantaneously reflected by the past securities prices. Therefore, the investors cannot obtain the abnormal gain on the basis of the past historical price information. If the stock prices are uncorrelated, they follow the random walk model. Thus autocorrelation function is used for measuring the dependence of successive terms in a set of stock returns of the DSE. To test the random walk or weak form efficiency hypothesis we use a very popular unit-root test named the Augmented Dickey-Fuller (ADF) test.However, some studies argue that in some situations ADF has low power (Diebold & Rudebusch 1991 and DeJong *et al*. 1992). Moreover, according to Kwiatkowski *et al.* (1992), classical hypothesis testing hardly allow the null hypothesis of unit root to be rejected unless there is strong evidence against it. To put it differently, if the time series under consideration does not have enough information, the null hypothesis of unit root is unlikely to be rejected against the alternative hypothesis of stationarity even if the time series is really stationary. Therefore, it is recommended to conduct confirmatory analysis, which implies testing of both the null hypothesis of a unit root and the null hypothesis of stationarity. That is why, we perform Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test developed by Kwiatkowski *et al.*(1992) along with ADF test.We also use the ARIMA (p, d, q) model in order to decompose our information variables into their anticipated and unanticipated components.

Finally, in order to see risk-return relationship, we examine the stochastic process over the study period employing models of conditional variances using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) formulation. The GARCH approach allows for an empirical assessment of the relationship between risk and returns in a setting that is consistent with the characteristics of leptokurtosis and volatility clustering observed in emerging stock markets. The Autoregressive Conditional Heteroscedasticity (ARCH) model introduced by Engle (1982) allows the variance of the error terms to vary over time, in contrast to the standard time series regression models, which assume a constant variance. Bollerslev (1986) generalized the ARCH process by allowing for a lag structure for the variance. Bollerslev (1986) allows the conditional variance to be a function of prior period's squared errors as well as its past conditional variances. The GARCH model has the advantage of incorporating heteroscedasticity into the estimation procedure. All GARCH models are martingale difference implying that all expectations are unbiased. The GARCH models are capable of capturing the tendency for volatility clustering in financial data. Volatility clustering in stock returns implies that large (small) price changes follow large (small) price changes of either sign.

5. Descriptive Statistics

Descriptive statistics for stock returns are presented in Table 1[1].

Table 1: Descriptive Statistics for stock returns

Statistics	DSE Returns
Mean (In Percent)	-0.0544336
Median (In Percent)	-0.0920714
Standard Deviation (In Percent)	1.68947
Coefficient of Variation	31.0372
Minimum	-0.203821
Maximum	0.0932997
Skewness	-0.793743
Excess Kurtosis	15.6166
JB Test for Normality	21785.7 (p-value 0)
Observations	2123

Source: Authors' Calculation

Both the mean and median returns are negative for DGEN. It means that most of the companies are running financial losses or lackluster returns on an investment during a specific period of time or some businesses are at their very early stages in the stock market and these new business are yet to begin making profits as the amount of capital that initially goes into the business to get it off the ground. The returns display negative skewness, meaning a greater chance of extremely negative outcomes for investors. A negatively skewed distribution provides the necessary environment for many small wins, as the majority of incidences are to the right (Morel, 2010). The reasons for this can be explained by prospect theory, which hypothesizes that investors receive decreasing reward for further gains. However, it is still unclear why skewness exists though several compelling arguments have been made; including, good/bad news asymmetry, price discovery, prospect theory and uncertainty of information. Negative skew had been shown to receive higher expected returns. It is generally believed that rational investors have a preference for positive skew; however, evidence of supporting a negative skew also exists.

The excess kurtosisis about 16 implies a leptokurtic distribution. That means there is a higher than normal probability of big positive and negative returns realizations. In other words, the distribution of DSE stock returns tends to overestimate the probability of achieving the mean return. This also implies high volatility of return. Moreover, it signals that the probability of obtaining an extreme value in the future is relatively high. Therefore, the negative skewness and leptokurtosis together indicate observing negative returns in greater magnitude with higher probability than implied by the normal distribution. Finally, the hypothesis of normality (unconditional) is rejected by Jarque-Bera test, confirming that the distribution of stock returns has either skewness or kurtosis or both.

6. Discussion of Tests Results

6.1 Test of Stationarity

6.1.1 Graphical Analysis

To have an initial idea about the likely nature of the time series, we plot the data in Figure 1. Visual inspection of the plot suggests that the mean and variance of stock price are time varying. That means the stock price series appears not to be stationary.

Figure 1: Stock price index, DSE, Bangladesh

Source: http://www.dsebd.org/recent_market_information.php

6.1.2 Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF) and Correlogram:

Another test of stationarity is correlogram analysis, which includes ACF, PACF, and their graphical presentation. Table 2 reports ACF and PACF for up to 25 lags of DGEN. Also, corresponding correlogram plots are depicted in Figure 2 and Figure 3, respectively. It is clear from both the correlogram table and correlogram plots that ACF tapers off very slowly, and PACF is significant at lag 1. This pattern is quite consistent with random walk or nonstationarity.

Table 2: Correlogram for DGEN_Index

Lag	ACF	PACF	Q-statistics [p-value]
1	0.9987 ***	0.9987 ***	2120.5456 [0.000]
2	0.9974 ***	-0.0166	4236.4658 [0.000]
3	0.9962 ***	0.0553 **	6348.3699 [0.000]
4	0.9951 ***	0.0249	8456.5563 [0.000]
5	0.9939 ***	-0.0122	10560.8767 [0.000]
6	0.9928 ***	0.0141	12661.4561 [0.000]
7	0.9917 ***	0.0074	14758.3940 [0.000]
8	0.9907 ***	0.0105	16851.8065 [0.000]
9	0.9895 ***	-0.0397 *	18941.2562 [0.000]
10	0.9882 ***	-0.0588 ***	21026.0908 [0.000]
11	0.9868 ***	-0.0114	23106.2203 [0.000]
12	0.9856 ***	0.0233	25181.9952 [0.000]
13	0.9842 ***	-0.0210	27253.2403 [0.000]
14	0.9831 ***	0.0654 ***	29320.6253 [0.000]
15	0.9819 ***	-0.0119	31384.0764 [0.000]
16	0.9806 ***	-0.0390 *	33443.1473 [0.000]
17	0.9793 ***	-0.0265	35497.5116 [0.000]
18	0.9780 ***	0.0173	37547.3771 [0.000]
19	0.9766 ***	-0.0389 *	39592.3356 [0.000]
20	0.9752 ***	0.0015	41632.3910 [0.000]
21	0.9739 ***	0.0273	43667.8857 [0.000]
22	0.9726 ***	0.0061	45698.9786 [0.000]
23	0.9712 ***	-0.0303	47725.3874 [0.000]
24	0.9697 ***	-0.0533 **	49746.5182 [0.000]
25	0.9680 ***	-0.0635 ***	51761.6219 [0.000]

Source: Authors' calculation using software

Putting it differently, the most striking feature of the correlogram analysis is that the autocorrelation coefficients at various lags are very high (almost one) even up to a lag of 25. That is, a particular shock (random shock) never dies out which implies an infinite memory. We can derive the same conclusion from Ljung-Box (LB) statistic or Box-pierce Q statistic also. As the last column of Table 2 shows, the value of the LB statistic up to lag 25 is about 51761.6219. The probability of obtaining such an LB value under the null hypothesis that the sum of 25 squared estimated autocorrelation coefficients is zero is practically zero. Therefore, the conclusion is that the DGEN index series is nonstationary.

Figure 2: Correlogram plot (ACF) for DGEN Index

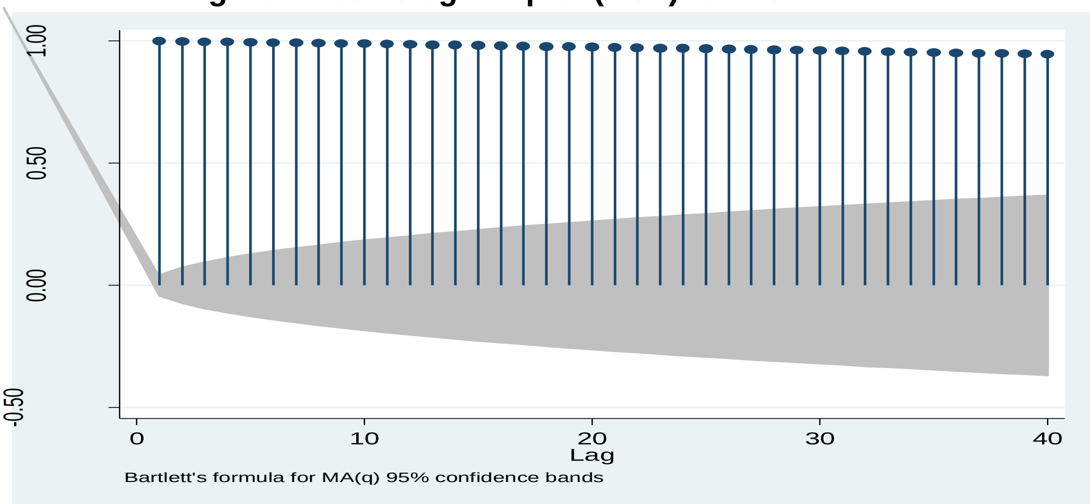
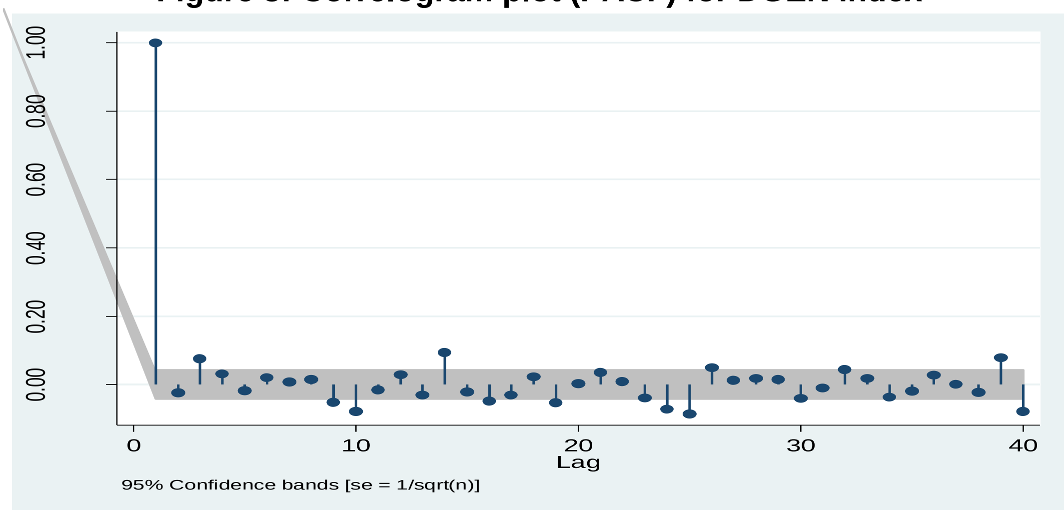


Figure 3: Correlogram plot (PACF) for DGEN index



6.1.3 Unit Root Test

As mentioned earlier, we test for unit root performing both ADF and KPSS tests. In our context, the ADF test consists of estimating the following regression:

$$\Delta I_t = \beta_1 + \delta I_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta I_{t-i} + \varepsilon_t, \quad (1)$$

Where I is DGEN, m is maximum lag length, and ε is the error term. On the other hand, the KPSS test involves the following regression:

$$I_t = \mu_t + v_t, \quad (2)$$

Where the error term v_t is assumed to be stationary and μ_t has a random walk representation:

$$\mu_t = \mu_{t-1} + \varepsilon_t; \quad \varepsilon_t \sim IID(0,\ \sigma_\varepsilon^2) \quad (3)$$

Since v_t is stationary, I_t will be stationary if μ_t is constant over time. In order for μ_t to be constant, σ_ε^2 needs to be zero. To put it differently, the null hypothesis of DGEN being stationary is $H_0: \sigma_\varepsilon^2 = 0$ as against the alternative hypothesis $H_a: \sigma_\varepsilon^2 > 0$.

We perform both tests with and without trend. Maximum lag length for both tests is determined following a criterion proposed by Schwert (1989).Results are reported in Table 3. The ADF null of nonstationarity cannot be rejected in both with- and without-trend models at any conventional level of significance. The KPSS null of stationarity, on the other hand, is rejected in both models at the 1% level of significance. Since both ADF and KPSS tests indicate nonstationarity in DGEN index, we can conclude with higher degree of certainty that the time series of stock price in the DSE is generated through a random walk process. All the approaches examined above provided uniform results regarding stationarity. Therefore, our findings reinforce the notion of efficient market hypothesis.

Table 3: Unit root test results

Model with	Test statistic		Null accepted/rejected		Stationary?
	ADF	KPSS	ADF	KPSS	
Trend	-2.391	0.609**	Accepted	Rejected	Non-stationary
No trend	-0.887	5.805**	Accepted	Rejected	Non-stationary

** Significant at the 1% level of significance

Figure 4: Time series plot for Return (R_t) of DSE

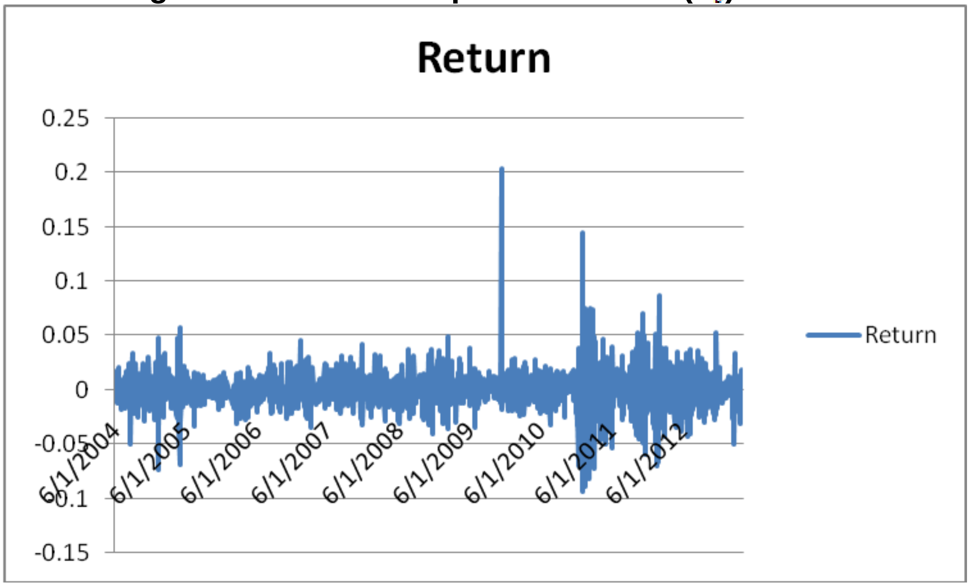


Table 4: ADF result of Stock Return (R_t) of DGEN index

Levels	τ_e	$p-value$	Type	$I(d)$
Without drift	-7.64258	4.059e-013	Stationary	$I(0)$
With drift	-7.73927	2.858e-012	Stationary	$I(0)$
With drift and trend	-7.82011	7.566e-012	Stationary	$I(0)$

6.2 Autoregressive Integrated Moving Average (ARIMA) Process

The AR process says that the forecast value of R_t at time *t* is simply some proportion (=α_i) of its value at different lags plus a random shock at time *t*; again the $R_t$values are expressed around their mean values. This process involves only the current and previous$R_t$values and there are no other regressors. In this sense, we can say that the "data speak for themselves." On the other hand, an MA process generates a series which at time t is equal to a constant plus a moving average of the current and past error terms.

A powerful process,$ARIMA(p,d,q)$, combines both of above possibilities with consideration of the order of integration of the series which can be modelled as:

$$\Delta R_t = \alpha_0 + \sum_{i=1}^{p} \pi_i \Delta R_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (4)$$

or,

$$R_t = \alpha_0 + \sum_{i=1}^{p} \pi_i R_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t. \quad (5)$$

Following the $Box-Jenkins\ (BJ)$ methodology we can decide about different orders of $ARIMA$. The simple ways of identification are the autocorrelation function (ACF), the partial autocorrelation function (PACF), and the resulting correlograms, which are given in the Table 5, Figure 5, and Figure 6 respectively.

Figure 5: Autocorrelation of Return in DSE

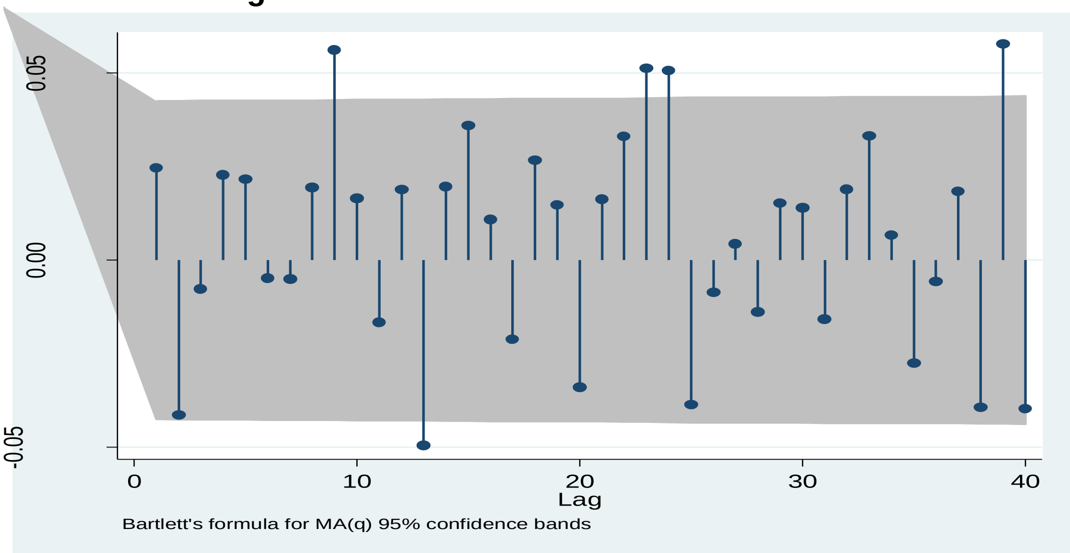
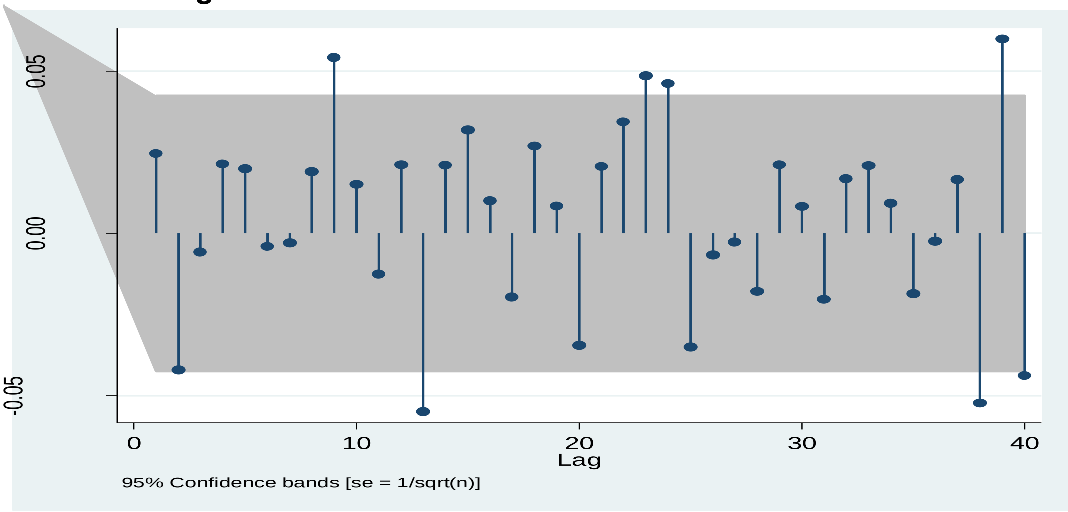


Figure 6: Partial autocorrelation of Return in DSE



From ACF, PACF, and Correlogram of the Index return it can be inferred that the pattern is quite different after taking the log first-difference of the index. In fact, there is a *sinusoidal* pattern observed here. In this case, it is not worthwhile to come up in a conclusion which ARIMA process best describes the data. Because of this sort of pattern, both AR and MA process might end up with the similar results. However, it will be verified later on by taking different models to describe the data applying a “trial and error” method. For now, it is evident from the correlogram that other than at lags 9, 13, 23, and 24autocorrelations are statistically not different from zero. The partial autocorrelations with spikes at lag 9, 13, 23, and 24 seem statistically significant but the rest are not. Let us therefore assume that the process generated the (log first-difference) Index is at most an AR (24) or MA (24) process. Of course, we do not have to include all the AR or MA terms up to 24. From the correlogram we know that only AR or MA terms at lag 9, 13, 23, and 24 are significant.

6.2.1 Estimation of the ARIMA Model:

As part of the model identification process, we observed different models following trial and error method. Results show that the ARIMA [AR lags of 9, 13, 23, and 24 with $I(1)$] fits the data well. The *p*-value of all the coefficient estimates are close to zero representing that all the estimates are significant at 5 percent level. It is also evident that applying the MA process (taking similar lags) instead of AR process provides the similar result because of the pattern of ACF and PACF of log first-difference of the data. This implies that, either of the models works well to fit the data. Therefore, without loss of generality, we can check only AR process from now on to test other possible models. Concerning the significance of estimates other models under consideration also are found suitable. Therefore, we need to compare all the models based on Information Criteria to represent the data well. The comparison is as follows:

Based on the Information Criteria, we can conclude that ARIMA [MA lags of 9, 13, 23,24 with *I*(1)] Process best fits data because it has the lowest values both for Akaike Criteria and Hannan-Quinn though it has the higher value for Schwarz Criteria compared to Model-3 and Model-4.Hence, our tentatively identified MA model is:

$$R_t = \theta + \beta_9 u_{t-9} + \beta_{13} u_{t-13} + \beta_{23} u_{t-23} + \beta_{24} u_{t-24} \quad (6)$$

Since all the four MA coefficients are statistically significant it can be interpreted that the stock return at time t is affected by its lag values at time $t-9, t-13, t-23,$ and $t-24$. All lag values save at lag 13 affects R_t positively.

Table 5: Autocorrelation function for return of DSE

Lag	ACF	PACF	Q-stat. [p-value]
1	0.0246	0.0246	1.2855 [0.257]
2	-0.0414 *	-0.0420 *	4.9320 [0.085]
3	-0.0077	-0.0057	5.0595 [0.167]
4	0.0228	0.0214	6.1612 [0.187]
5	0.0216	0.0200	7.1555 [0.209]
6	-0.0048	-0.0041	7.2047 [0.302]
7	-0.0051	-0.0029	7.2603 [0.402]
8	0.0193	0.0190	8.0580 [0.428]
9	0.0562 ***	0.0541 **	14.7913 [0.097]
10	0.0165	0.0151	15.3721 [0.119]
11	-0.0167	-0.0124	15.9643 [0.142]
12	0.0188	0.0210	16.7196 [0.160]
13	-0.0495 **	-0.0549 **	21.9515 [0.056]a
14	0.0196	0.0211	22.7763 [0.064]
15	0.0359 *	0.0318	25.5318 [0.043]
16	0.0108	0.0100	25.7832 [0.057]
17	-0.0212	-0.0196	26.7428 [0.062]
18	0.0266	0.0268	28.2572 [0.058]
19	0.0147	0.0082	28.7216 [0.070]
20	-0.0340	-0.0344	31.1959 [0.053]
21	0.0163	0.0207	31.7671 [0.062]
22	0.0330	0.0341	34.1022 [0.048]
23	0.0512 **	0.0482 **	39.7345 [0.016]
24	0.0506 **	0.0460 **	45.2338 [0.005]
25	-0.0387 *	-0.0350	48.4537 [0.003]

Table 6. ARIMA Model Comparison

Model	Akaike Criterion	Schwarz Criterion	Hannan-Quinn
ARIMA [AR lags of 9, 13, 23,24 with *I*(1)]:	-11308.33	-11280.03	-11298.34
ARIMA [MA lags of 9, 13, 23,24 with *I*(1)]:	-11308.70	-11280.40	-11298.34
ARIMA [AR lag of 9 with *I*(1)]:	-11298.48	-11287.16	-11294.33
ARIMA [AR lag of 9 and 13 with *I*(1)]:	-11301.76	-11284.78	-11295.54
ARIMA [AR lag of 9, 13, and 23 with *I*(1)]:	-11305.51	-11282.87	-11297.22

6.3 Measuring the Volatility and the GARCH

It is common for stock prices or returns that it often exhibits the phenomenon of time varying volatility clustering, that is, periods of wide swings followed by periods of relative calm. Volatility is very crucial for investors as high volatility could mean huge losses or gains and hence greater uncertainty. In volatile markets it is difficult for companies to raise capital in the capital markets.

In this section a generalized autoregressive conditional heteroscedastic (GARCH) modelling framework is used to analyse the significance of volatility effect on stock returns. This approach allows us for an empirical measurement of the relationship between risk and returns in a setting that is consistent with the characteristics of leptokurtic and volatility clustering observed in the time series of daily stock returns of DGEN. In this paper a generalized GARCH (p, q) model is utilized to model volatility and test for weak-form efficiency of the stock returns. In this section we outline the recent developments in modelling the conditional volatility of stock returns. Modelling of volatility has come a long way. A crude measure of volatility, standard deviation, is the standard tool applied in the financial markets. This measure estimates the sample standard deviation of the returns over a sample period. The problem with this approach lies with the choice of sample period. If the sample period is too long it may not be relevant for today and if it is too short, it will tend to be too noisy. Furthermore, an asset holder is concerned with the forecast of the rate of return and its variance over the holding period, the so-called conditional variance. He is least concerned with the long-run forecast of the variance, the so-called unconditional variance. One way to resolve the above problem is to resort to estimating rolling standard deviation. While this approach provides forecast of the conditional variance, its drawback is that it equally weighs average of the squared residuals over the pre-defined rolling window. Moreover, this approach is criticized on the grounds that it attaches a zero weight to observations that fall before the pre-defined rolling window. Engle (1982) proposed an autoregressive conditionally heteroscedastic (ARCH) model that allows the data to determine the best weights to use in forecasting the variance. The model specifies conditional volatility that incorporates the common sense logic that observations belonging to the recent past should get higher weights than those belonging to the distant past i.e. it adopts an unequal weighting structure that evolves according to an autoregressive scheme. If an autoregressive moving average (ARMA) process is assumed for the error variance, the process is a generalized autoregressive conditional heteroscedasticity (GARCH) model (Bollerslev 1986) which essentially generalizes the ARCH model. In that case the GARCH (p, q) can be represented for stock return volatility (σ_t^2) as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (7)$$
$$(q = ARCH, p = GARCH)$$
$$\varepsilon_t | \Psi_{t-1} \sim N(0, \sigma_t^2)$$

In this system, equation (5) is known as variance equation. The choice of p, q and J are identified using standard time series techniques AIC and SBIC criteria. Following the iterative technique we run $GARCH(1,1)$, $GARCH(1,2)$, $GARCH(2,1)$, and $GARCH(2,2)$ and found $GARCH(1,2)$ more appropriate as it has the lowest AIC value (-12007.97). The $GARCH(1,2)$ results have been represented in the Table 7. The estimates reject the hypothesis of time-invariant conditional volatility for stock returns of DSE. From the estimated results in Table 7 it has been found that the estimated parameters α_i and β_j are significant at any significance level. The significance of α_i, and β_j supports the hypothesis that the conditional volatility changes over times due to volatility clustering effect, as implied by a significant α_1 and α_2 and due to temporal dependence is reflected by the significant β_1. That is the errors in the model exhibit conditional heteroscedasticity. Hence, the market is expected to demand a higher risk premium for higher risk, the higher conditional variability could cause higher returns. Unlike other studies, this study found consistent results regarding significance and sign of the risk-return parameter estimates. Furthermore the condition $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$ indicates the stability of the model.

Table 7: GARCH (1,2) results

Model: GARCH, using observations 2004/06/02-2010/03/24 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Hessian

	Coefficient	*Std. Error*	*Z*	*p-value*	
alpha(0)	1.98736e-05	3.69035e-06	5.3853	<0.00001	***
alpha(1)	0.20432	0.0322947	6.3267	<0.00001	***
alpha(2)	0.124369	0.0433073	2.8718	0.00408	***
beta(1)	0.647833	0.0384945	16.8292	<0.00001	***

Mean dependent var	-0.000544	S.D. dependent var	0.016895
Log-likelihood	5995.854	Akaike criterion	-11981.71
Schwarz criterion	-11953.41	Hannan-Quinn	-11971.35

Unconditional error variance = 0.000846459

7. Conclusion and Policy Recommendations

The stock market acts as the main source of corporate financing and fund raising in today's world. In fact, it reflects the strength of the economy of a country. An active stock market can play a vital role to enhance the economic growth and sustainable development of a developing country like Bangladesh. However, the current study was carried out to investigate the market efficiency of the DSE, the pattern of stock return in it, and the relationship between returns and volatility using the GARCH model. The empirical research finds that, the stock returns of DSE are negatively skewed, leptokurtic and therefore not normally distributed. The outcomes of ACF, ADF, and KPSS tests and ARIMA models uphold the findings of some previous studies showing the existence of weak-form market efficiency in the pricing of equities. The findings also establish significant positive relationship between risk and return for DSE, while the previous studies found inconsistent results, significant but negative relationships between risk and returns. Thus, it can be deduced that the portfolio theory applies for stock price index at DSE. Still there are rooms for improving the capital market efficiency in Bangladesh. A policy of timely effective disclosure and dissemination of information to shareholders and investors on the performance of listed companies may be highly emphasized. Creating corruption free and investor friendly regulatory frameworks also should have priority to improve the DSE into a well-developed one in the long-run. It is necessary to maintain market discipline and continue reforms in the legal frameworks to support financial development and to restore the investors' confidence. The concerned authority must cope with the continuously changing global economy for maintaining the efficient capital market in Bangladesh.

Endnotes

[1]In this paper, stock returns R_t are defined as continually compounded (or log) returns at time t, which is calculated as the natural log difference in the closing market price index between two dates and expressed it as percentage, is given by $R_t = \ln\left(\frac{PI_t}{PI_{t-1}}\right) \times 100$ where PI_t is the price index at time t and PI_{t-1} is the price index at time t-1.

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Appendix

A.1. ARIMA [AR lags of 9, 13, 23, 24 with $I(1)$]

Model 1: ARMA, using observations 2004/06/02-2013/04/15 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Outer Products matrix

	Coefficient	*Std. Error*	*Z*	*p-value*	
AR(9)	0.0552979	0.0216291	2.5566	0.01057	**
AR(13)	-0.0499687	0.0216478	-2.3083	0.02098	**
AR(23)	0.0508146	0.0216704	2.3449	0.01903	**
AR(24)	0.0474624	0.0216803	2.1892	0.02858	**

Mean dependent var	0.000544	S.D. dependent var	0.016895
Mean of innovations	0.000487	S.D. of innovations	0.016808
Log-likelihood	5659.166	Akaike criterion	-11308.33
Schwarz criterion	-11280.03	Hannan-Quinn	-11297.97

A.2. ARIMA [MA lags of 9, 13, 23,24 with I(1)]:

Model 2: ARMA, using observations 2004/06/02-2013/04/15 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Outer Products matrix

	Coefficient	*Std. Error*	*Z*	*p-value*	
MA(9)	0.0519046	0.0216303	2.3996	0.01641	**
MA(13)	-0.0546128	0.0216467	-2.5229	0.01164	**
MA(23)	0.0500599	0.0216774	2.3093	0.02093	**
MA(24)	0.0507655	0.0216812	2.3414	0.01921	**

Mean dependent var	0.000544	S.D. dependent var	0.016895
Mean of innovations	0.000495	S.D. of innovations	0.016807
Log-likelihood	5659.352	Akaike criterion	-11308.70
Schwarz criterion	-11280.40	Hannan-Quinn	-11298.34

A.3. ARIMA [AR lag of 9 with *I*(1)]:

Model 3: ARMA, using observations 2004/06/02-2013/04/15 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Outer Products matrix

	Coefficient	*Std. Error*	*Z*	*p-value*	
AR(9)	0.0570169	0.0216855	2.6293	0.00856	***

Mean dependent var	0.000544	S.D. dependent var	0.016895
Mean of innovations	0.000514	S.D. of innovations	0.016872
Log-likelihood	5651.239	Akaike criterion	-11298.48
Schwarz criterion	-11287.16	Hannan-Quinn	-11294.33

A.4. ARIMA [AR lag of 9 and 13 with *I*(1)]:
Model 4: ARMA, using observations 2004/06/02-2013/04/15 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Outer Products matrix

	Coefficient	*Std. Error*	*Z*	*p-value*	
AR(9)	0.0581531	0.0216639	2.6843	0.00727	***
AR(13)	-0.0498094	0.0216961	-2.2958	0.02169	**

Mean dependent var	0.000544	S.D. dependent var	0.016895
Mean of innovations	0.000541	S.D. of innovations	0.016851
Log-likelihood	5653.880	Akaike criterion	-11301.76
Schwarz criterion	-11284.78	Hannan-Quinn	-11295.54

A.5. ARIMA [AR lag of 9, 13, and 23 with *I*(1)]:
Model 5: ARMA, using observations 2004/06/02-2013/04/15 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Outer Products matrix

	Coefficient	*Std. Error*	*Z*	*p-value*	
AR(9)	0.0570718	0.021639	2.6374	0.00835	***
AR(13)	-0.0507794	0.0216699	-2.3433	0.01911	**
AR(23)	0.0518765	0.021689	2.3918	0.01676	**

Mean dependent var	0.000544	S.D. dependent var	0.016895
Mean of innovations	0.000513	S.D. of innovations	0.016828
Log-likelihood	5656.756	Akaike criterion	-11305.51
Schwarz criterion	-11282.87	Hannan-Quinn	-11297.22

A.6. GARCH (1,2) results
Model: GARCH, using observations 2004/06/02-2010/03/24 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Hessian

	Coefficient	*Std. Error*	*Z*	*p-value*	
alpha(0)	1.98736e-05	3.69035e-06	5.3853	<0.00001	***
alpha(1)	0.20432	0.0322947	6.3267	<0.00001	***
alpha(2)	0.124369	0.0433073	2.8718	0.00408	***
beta(1)	0.647833	0.0384945	16.8292	<0.00001	***

Mean dependent var	-0.000544	S.D. dependent var	0.016895
Log-likelihood	5995.854	Akaike criterion	-11981.71
Schwarz criterion	-11953.41	Hannan-Quinn	-11971.35

Unconditional error variance = 0.000846459

A.7. GARCH, using observations 2004/06/02-2010/03/24 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
alpha(0)	1.98736e-05	3.69035e-06	5.3853	<0.00001	***
alpha(1)	0.20432	0.0322947	6.3267	<0.00001	***
alpha(2)	0.124369	0.0433073	2.8718	0.00408	***
beta(1)	0.647833	0.0384945	16.8292	<0.00001	***

Mean dependent var	-0.000544	S.D. dependent var	0.016895
Log-likelihood	5995.854	Akaike criterion	-11981.71
Schwarz criterion	-11953.41	Hannan-Quinn	-11971.35

Unconditional error variance = 0.000846459

A.8.GARCH, using observations 2004/06/02-2010/03/24 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
alpha(0)	1.65029e-05	2.86924e-06	5.7516	<0.00001	***
alpha(1)	0.264473	0.0289054	9.1496	<0.00001	***
beta(1)	0.711256	0.0249396	28.5191	<0.00001	***

Mean dependent var	-0.000544	S.D. dependent var	0.016895
Log-likelihood	5991.288	Akaike criterion	-11974.58
Schwarz criterion	-11951.93	Hannan-Quinn	-11966.29

Unconditional error variance = 0.000679938

A.9. GARCH, using observations 2004/06/02-2010/03/24 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
alpha(0)	2.48328e-05	5.0928e-06	4.8761	<0.00001	***
alpha(1)	0.199296	0.0319928	6.2294	<0.00001	***
alpha(2)	0.21461	0.0633185	3.3894	0.00070	***
beta(1)	0.358563	0.168484	2.1282	0.03332	**
beta(2)	0.199047	0.119558	1.6649	0.09594	*

Mean dependent var	-0.000544	S.D. dependent var	0.016895
Log-likelihood	5996.714	Akaike criterion	-11981.43
Schwarz criterion	-11947.47	Hannan-Quinn	-11969.00

Unconditional error variance = 0.000871831

A.10. GARCH, using observations 2004/06/02-2010/03/24 (T = 2122)
Dependent variable: ld_DGEN_Index
Standard errors based on Hessian

	Coefficient	*Std. Error*	*z*	*p-value*	
alpha(0)	1.41511e-05	2.61782e-06	5.4057	<0.00001	***
alpha(1)	0.259291	0.0312365	8.3009	<0.00001	***
beta(1)	0.725852	0.115728	6.2721	<0.00001	***
beta(2)	1.04664e-012	0.0978781	0.0000	1.00000	

Mean dependent var	-0.000544	S.D. dependent var	0.016895
Log-likelihood	5990.917	Akaike criterion	-11971.83
Schwarz criterion	-11943.53	Hannan-Quinn	-11961.47

Unconditional error variance = 0.000952524