Forecasting Volatility of Stock Indices with ARCH Model

Md. Zahangir Alam[1], Md. Noman Siddikee[1] & Md. Masukujjaman[2]

[1] Department of Business Administration, International Islamic University Chittagong, Dhaka Campus, Bangladesh

[2] Department of Business Administration, Northern University, Bangladesh

Correspondence: Md. Zahangir Alam, Assistant Professor of Finance, Department of Business Administration, International Islamic University Chittagong, Dhaka Campus, House # 27(1st Floor), Road # 03, Dhanmondi R/A, Dhaka-1205, Bangladesh. Tel: 880-196-060-8339. E-mail: mzafinance@gmail.com

Received: December 25, 2012 Accepted: January 18, 2013 Online Published: April 8, 2013

doi:10.5430/ijfr.v4n2p126 URL: http://dx.doi.org/10.5430/ijfr.v4n2p126

Abstract

The main motive of this study is to investigate the use of ARCH model for forecasting volatility of the DSE20 and DSE general indices by using the daily data. GARCH, EGARCH, PARCH, and TARCH models are used as benchmark models for the study purpose. This study covers from December 1, 2001 to August 14, 2008 and from August 18, 2008 to September 10, 2011 as in-sample and out-of-sample set sets respectively. The study finds the past volatility of both the DSE20 and DSE general indices returns series are significantly, influenced current volatility. Based on in-sample statistical performance, both the ARCH and PARCH models are considered as the best performing model jointly for DSE20 index returns, whereas for DSE general index returns series, ARCH model outperforms other models. According to the out – of- sample statistical performance, all models except GARCH and TARCH models are regarded as the best model jointly for DSE20 index returns series, while for DSE general index returns series, no model is nominated as the best model individually. Based on the in-sample trading performance, all models except GARCH are considered as the best model jointly for DSE20 index returns series, while ARCH model is selected as the best model for DSE general index returns series. A per outputs of out-of-sample trading performance, the EGARCH model is the best performing model for DSE20 index returns series, whereas the GARCH and ARCH models are considered as the best performing model jointly for DSE general index returns series.

Keywords: forecasting, volatility, ARCH, GARCH, EGARCH, PARCH, TARCH

1. Introduction

Forecasting of the stock exchange index is a motivating and tricky issue for both for investors and academics. The stock market is an extremely nonlinear vibrant system whose performance is manipulated by a number of factors, namely inflation rates, interest rates, economic atmosphere, political issues, and so on (Sutheebanjard and Premchaiswadi, 2010). In generic sense, financial markets and in particular sense, stock markets are characterized by uncertainty. The prices of financial securities, which are traded in the financial markets as well as interest rate and foreign exchange rates, are horizontal to constant inconsistency. For this type of changeability, their returns over the various periods of time are notably volatile and complicated to forecast. Volatility is an important variable for appraising the status of a financial market as well as for taking decision by its participants, like investors, investment managers, speculators and the financial supervisory body (Panait and Slăvescu, 2012). Forecasting volatility is a crucial and exigent financial matter, which have attained much concentration. It is broadly consented that though returns of financial securities prices are more or less unpredictable on daily as well as monthly basis, return volatility is forecastable, phenomenon along with vital inference for financial economics and risk management (Torben *et al.* 2009). Precise volatility forecasts are essential to traders, investors, financial analyst and researchers who are interested in realizing stock market dynamics (Ederington and Guan, 2005). Trading in stock market indices has achieved unparalleled attractiveness all over the world. The increasing diversity of financial index related instruments, along with economic growth enjoyed in the last few years, has broaden the dimension of global investment opportunity to both the individual and institutional investors. Index trading vehicles give an effectual way for the investors for hedging against prospective market risks as well as they generate new return making opportunities for market arbitragers and speculators. Therefore, being able to appropriately forecasting of stock index has thoughtful inference and important to researchers and practitioners identical (Leung et al. 2000). To conduct a study on stock market is a severe and challenging monetary activity. Enormous return may be earned through extremely accurate predictions by using a suitable forecasting model, however aggressive fluctuations in the stock market activity make forecasting as a tricky issue. So, forecasting accuracy is a most important concern of numerous investors, highlighting the magnitude of structuring a more appropriate forecasting model (Chang *et al.* 2009). The stock market is a set of connections that gives a platform for about each economic transaction in the business world at a dynamic rate entitled the stock value that is based on the market equilibrium. Forecasting this stock value offers huge arbitrage profit opportunities, which are the main motivation for doing research in this field (Gupta and Dhingra, n.d.). Volatility is a vital factor for determining price of financial instruments like stocks, options, and futures, is a measure of trade-off between risk and return on an investment. The volatility of stock market has a significant influence on financial rules and regulations, monetary and fiscal policies as well. The realistic significance of modelling and forecasting volatility in various finance applications represent that the accomplishment or failure of volatility models depend upon the features of experimental data which they attempt to capture and forecast. Volatility of share market is a crucial issue for the government's policy makers, market analysts, corporate and financial managers, since a remarkable volatility in a share market leads to an adverse impact for a country's economy (Islam *et al.* 2012).

The key motivation of the study is to forecast volatility of the stock indices with ARCH class model.

2. Literature Review

Islam *et al.* (2012) conduct a study on forecasting volatility of Dhaka stock exchange by using linear as well as non-linear models and find that among linear model, the moving average model occupies first position according to root mean square error, mean absolute error, Theil-U and linex loss function criteria. They also find that non-linear models do not outperform linear models based on various error measurement criteria and moving average model nominates as the best model. Sutheebanjard and Premchaiswadi (2010) reveal that the projected prediction function not only yields the lowest MAPE for short-term periods but also yields a MAPE lesser than 1% for long-term periods. Dunis, Laws and Karathanasopoulos (2011) state that the mixed -HONNs and the mixed RNNs models carry out outstandingly as well and appear to have an capability in giving superior forecasts when autoregressive series are only applied as inputs. Louzis, Sisinis, and Refenes (2010) mention that compared with recognized HAR and Autoregressive Fractionally Integrated Moving Average (ARFIMA) realized volatility models, the proposed model shows superior in-sample fitting, as well as , out-of-sample volatility forecasting performance. According to Panait and Slăvescu (2012), the GARCH-in-mean model is unsuccessful to validate the theoretical hypothesis that there is a positive relationship between volatility and future returns, principally due to the variance coefficient from the mean equation of the model is not statistically significant for the majority of the time series analyzed and on most of the frequencies. MCMillan, Speight and Apgwilym (2000) reveal that the random walk model gives immensely better monthly volatility forecasts, whereas random walk, moving average and recursive smoothing models present moderately better weekly volatility forecast, and GARCH, moving average and smoothing models produce marginally better daily forecasts. Lee, Chi, Yoo and Jin (2008) find that among Back Propagation Neural Network (BPNN), Bayesian Chiao's (BC), and SARIMA models, the SARIMA model is nominated as the best model for mid-term and long-term forecasting, whereas BC model is selected as the best model for short-term forecasting. Chen (2011) reveals that the total index in terms of percentage is ten times that of the buy-and-hold method and two times that of Wang and Chan's (2007) model. Al-Zeaud (2011) conducts a study on modelling and forecasting volatility using ARIMA model and reveals that ARIMA (2,0,2) is the best model for banking sector, since this model provides the lowest mean square error followed by ARIMA (1,1,1). Leung, Daouk and Chen (2000) find that the classification model beat the level estimation model in the light of forecasting the direction of the stock market movement and maximizing returns from investment trading. Chang, Wei and Cheng (2009) demonstrate that the proposed model is better than the listing methods in respect of root mean square error. Yalama and Sevil (2008) reveal that the asymmetric volatility class models outperform the historical model for forecasting stock market volatility. According to Mehrara, Moeini, Ahrari and Ghafari (2010), the exponential moving average model beat the simple moving average model as well as the Group Method of Data Handling do better than Multi-Layered Feed Forward network model for forecasting stock price index. Tang, Yang and Zhou (2009) reveal that the proposed algorithm can assist to get better the performance of normal time series analysis in stock price forecasting significantly.

3. Methodology

3.1 Data

Only the time series data is used in this study consists of the Dhaka Stock Exchange (DSE) indices, namely DSE20 Index and DSE General Index. The requisite data is obtained from the DSE library for the study purpose. The study period covers from December 1, 2001 to September 10, 2011 which contains 2600 trading days. The total data set is divided into in-sample and out-of-sample data set. The in-sample data set covers from December 1, 2001 to August 14, 2008 and includes 1733 observations, whereas out-of-sample covers from August 18, 2008 to September 10, 2011 and incorporates 867 observations.

3.2 Jarque-Bera Statistics

Jarque-Bera statistics is applied to examine the non-normality of the DSE20 and DSE general stock indices.

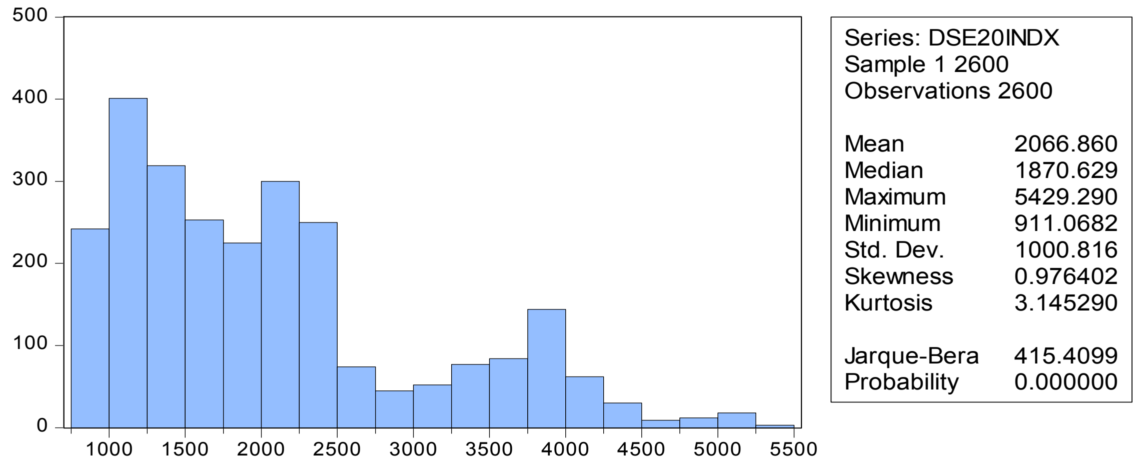


Figure 1. DSE20 index summary statistics

Figure 1 reveals that a positive skewness, 0.976402, and a high positive kurtosis, 3.145290. As per the Jarque-Bera statistics, DSE20 index is non-normal at the confidence interval of 99%, since probability is 0.0000 which is less than 0.01. So, it is mandated to convert the DSE20 index series into the return series.

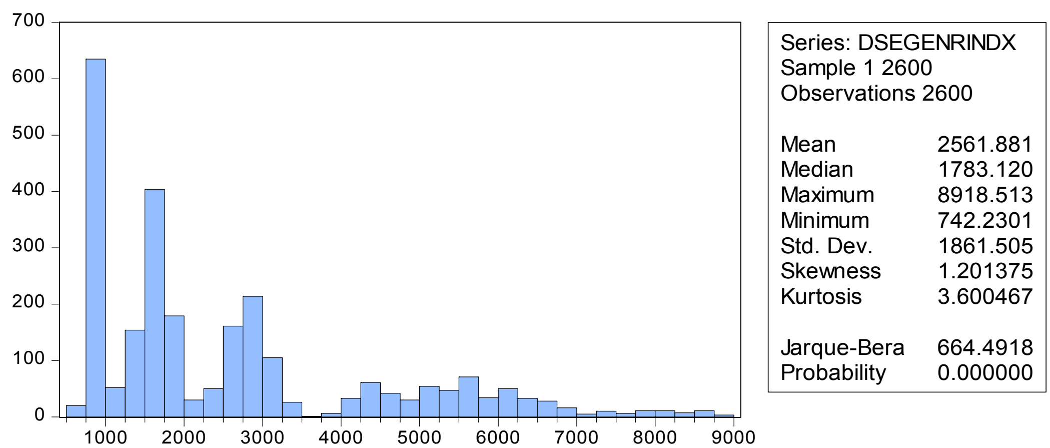


Figure 2. DSE general index summary statistics

Figure 2 demonstrates that a positive skewness, 1.201375 as well as a positive kurtosis, 3.600467. As per Jarque-Bera statistics, the DSE general index is non-normal at the confidence interval of 99%, since probability is 0.0000 which is less than 0.01. So, it is also needed to convert the DSE general index series into the return series.

3.3 Transformation of the DSE20 Index and DSE General Index Series

In general, the movements of the stock indices series are non-stationary, quite random and not appropriate for the study purpose. The series of DSE20 index and DSE general index are transformed into returns by using the following equation:

$$R_t = \left(\frac{P_t}{P_{t-1}}\right) - 1 \quad (1)$$

Where,

R_t = the rate of return at time t

P_t = the stock index at time t

P_{t-1} = the stock index just prior to the time t

3.4 Augmented Dickey-Fuller (ADF) Test and Phillips-Perron (PP) Test on DSE20 Index and DSE General Index Returns Series

ADF test as well as PP test are used to get confirmation regarding whether BDT/USD exchange rates return series is stationary or not.

Table 1. ADF test on DSE20 index returns and DSE general index returns

		t-Statistic		Prob.*	
		DSE20INDX	DSEGINDX	DSE20INDX	DSEGINDX
Augmented Dickey-Fuller test statistic		-47.23678	-49.67511	0.0001	0.0001
	1% level	-3.432673	-3.432673		
	5% level	-2.862452	-2.862452		
Test critical values:	10% level	-2.567301	-2.567301		

*MacKinnon (1996) one-sided p-values.

Table 1 shows that the values of ADF test statistic, -47.23678, is less than its test critical value, -2.862452, at 5%, level of significance which implies that the DSE20 index return series is stationary. An outcome of ADF test confirms that the DSE general index return series is stationary, because the values of ADF test statistic is less than its test critical value.

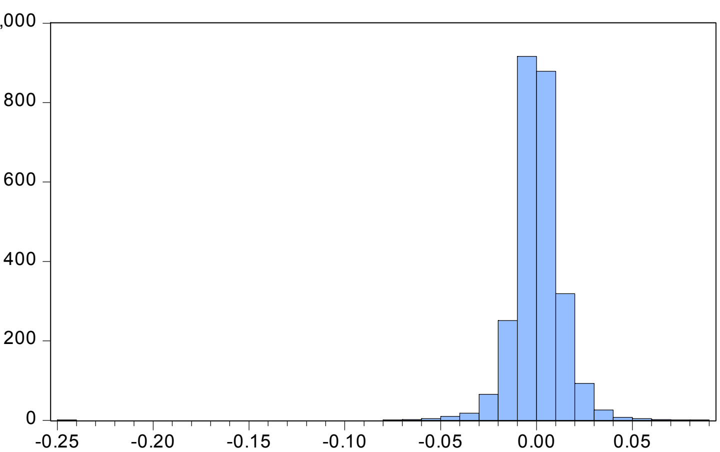
Table 2. PP test on DSE20 index returns and DSE general index returns

		t-Statistic		Prob.*	
		DSE20INDX	DSEGINDX	DSE20INDX	DSEGINDX
Phillips-Perron test statistic		-47.43146	-49.90572	0.0001	0.0001
	1% level	-3.432673	-3.432673		
	5% level	-2.862452	-2.862452		
Test critical values:	10% level	-2.567301	-2.567301		

*MacKinnon (1996) one-sided p-values.

Table 2 illustrates the results of the PP test and proves that the DSE20 index returns series is stationary, because the values of PP test statistic, -47.43146, **is** less than its test critical value, 2.862452, at the level of significance of 5%. The findings of the PP test also confirms that the DSE general index returns series is stationary, since the values of PP test statistic is less than its test critical value.

3.5 Summary Statistics of the DSE20 Index Returns and DSE General Index Returns



Series: RDSE20INDX	
Sample 1 2600	
Observations 2600	
Mean	0.000521
Median	0.000213
Maximum	0.089096
Minimum	-0.249456
Std. Dev.	0.013204
Skewness	-2.494639
Kurtosis	55.38307
Jarque-Bera	299961.9
Probability	0.000000

Figure 3. DSE20 index returns summary statistics

Figure 3 reveals a negative skewness, -2.494639, and a positive kurtosis, 55.38397. As per the Jarque-Bera statistics, the DSE20 index returns series is non-normal at 95% confidence level, since probability is 0.0000 which is less than 0.05.

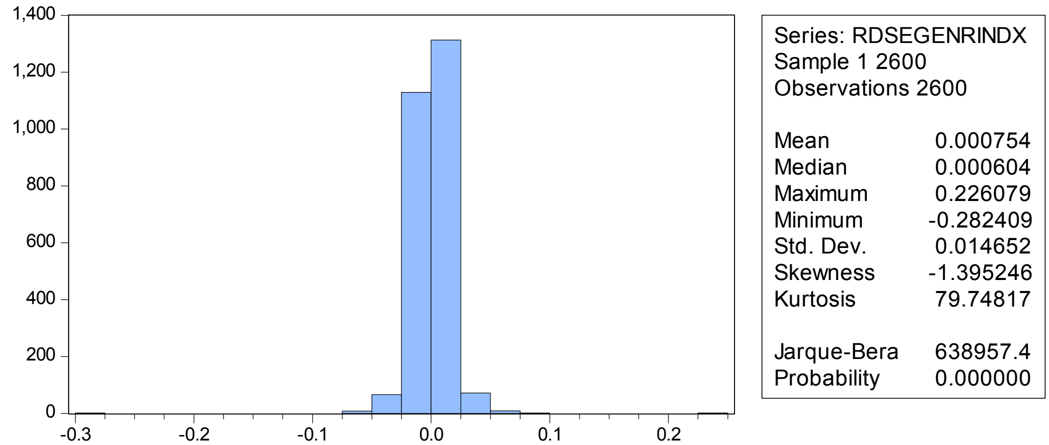


Figure 4. DSE general index returns summary statistics

Figure 4 also reveals a negative skewness, -1.395246, and a positive kurtosis, 79.74817. Based on the Jarque-Bera statistics, the DSE general index returns series is non-normal at 5% level of significance, because the probability, 0.0000, is less than 0.05.

3.6 Specification of the Models Used in This Study

3.6.1 Benchmark Model

ARCH model is benchmarked with GARCH, EGARCH, PARCH, and TARCH models in this study.

3.6.1.1 GARCH Model

GARCH model is developed by Bollerslev (1986) & Taylor (1986) independently and according to this model the conditional variance to be dependent upon previous own lags. The form of this model is given below:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2}$$

3.6.1.2 EGARCH Model

EGARCH) model is developed by Nelson (1991). The conditional variance equation can be presented in the following form:

$$\ln\sigma_t^2 = \omega + \beta \ln\sigma_{t-1}^2 + \gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] \tag{3}$$

3.6.1.3 PARCH Model

The PARCH model is an extension of the GARCH model with an additional term added to account for possible asymmetries (Brooks, 2008). The conditional variance is now given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{4}$$

3.6.1.4 TARCH Model

Zakoïan (1994) & Glosten *et al*. (1993) use the TARCH model with an intention of independence than for the asymmetric effect of the "news" (Brooks, 2008). Form of this model is as follows:

$$\sigma_t^2 = \omega + \sum_{j=1}^{p}\beta_j\,\sigma_{t-j}^2 + \sum_{i=1}^{q}\alpha_i\,u_{t-i}^2 + \sum_{k=1}^{r}\gamma_k\,u_{t-k}^2\,\overline{I_{t-k}} \tag{5}$$

3.6.2 ARCH Model

It is a non-linear model which does not assume that the variance is constant, and it describes how the variance of the errors evolves. Many series of financial asset returns that provides a motivation for the ARCH class of models, is known as 'volatility clustering' or 'volatility pooling'. Volatility clustering describes the tendency of large changes in asset prices (of either sign) to follow large changes and small changes (of either sign) to follow small changes.

Under the ARCH model, the 'autocorrelation in volatility' is modelled by allowing the conditional variance of the error term, δ_t^2 , to depend on the immediately previous value of the squared error and ARCH(1) model takes the following form (Brooks, 2008):

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \quad (6)$$

The form of ARCH (q) model is as follows where error variance depends on q lags of squared errors:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots\cdots + \alpha_q u_{t-q}^2 \quad (7)$$

3.7 Statistical and Trading Performance of the Model

3.7.1 Measures of the Statistical Performance of the Model

The statistical performance measures, like mean absolute error (MAE); mean absolute percentage error (MAPE); root mean squared error (RMSE); and theil-u, are applied to pick the best performing model both in the in-sample data set and the out-of-sample data set independently in this study. There is a negative association between the forecasting volatility accuracy of the model and the output of RMSE, MAE, MAPE and theil-U.

3.7.2 Measures of the Trading Performance of the Model

The trading performance measures, namely annualized return (R^A); annualized volatility(σ^A); Sharpe ratio (SR); and maximum drawdown (MD), are applied to pick the best model. The values of annualized return and Sharpe ratio are positively associated with the forecasting volatility accuracy of a given model, whereas annualized volatility and maximum drawdown are inversely associated.

4. Empirical Results

4.1 ARCH Model

Table 3. Output of ARCH model on DSE20 index return

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000588	0.000327	1.796475	0.0724
		Variance Equation		
C	0.000136	6.30E-07	216.3510	0.0000
RESID(-1)^2	0.222378	0.020218	10.99896	0.0000

Table 4. Output of ARCH model on DSE general index return

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000293	0.000259	1.131417	0.2579
		Variance Equation		
C	0.000157	9.64E-07	163.0593	0.0000
RESID(-1)^2	0.345453	0.025560	13.51550	0.0000

The outputs of ARCH model on DSE20 index and DSE general index show that the constant, C, is not statistically significant both in the mean and variance equations, since the probability of C is greater than 0.00. The variance equation illustrates that RESID(-1)^2 term is also statistically significant at 1% level of significance which implies that the volatility of risk is influenced by past square residual terms. Therefore, it can be mentioned that the past volatility of both the DSE20 index and DSE general index is significantly, influencing the current volatility.

4.2 GARCH Model

Table 5. Output of GARCH model on DSE20 index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.59E-05	0.000211	-0.075233	0.9400
		Variance Equation		
C	3.97E-06	2.57E-07	15.45235	0.0000
RESID(-1)^2	0.158877	0.011755	13.51586	0.0000
GARCH(-1)	0.840005	0.008207	102.3540	0.0000

Table 6. Output of GARCH model on DSE general index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.764238	2757.931	0.001727	0.9986
		Variance Equation		
C	1.76E-06	3.60E-07	4.881778	0.0000
RESID(-1)^2	0.318826	0.015093	21.12347	0.0000
GARCH(-1)	0.794913	0.004796	165.7431	0.0000

The outputs of the GARCH model on DSE20 index and DSE general index illustrate that the constant, C, is not statistically significant both in the mean and variance equations. The variance equation describes that the RESID(-1)^2 term is statistically significant at both the DSE20 and DSE general indices returns which imply that the volatility of risk is influenced by past square residual terms. The GARCH (-1) term is also statistically significant in the both indices. So, it can be mentioned that the past volatility of both the DSE20 index and DSE general index is significantly, influencing the current volatility.

4.3 EGARCH Model

Table 7. Output of EGARCH model on DSE20 index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.74E-05	0.000240	0.239442	0.8108
		Variance Equation		
C(4)	-0.346061	0.027068	-12.78504	0.0000
C(5)	0.216456	0.015061	14.37157	0.0000
C(6)	0.029801	0.007039	4.233534	0.0000
C(7)	0.978565	0.002021	484.2629	0.0000

Table 8. Output of EGARCH model on DSE general index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000366	0.000414	0.884059	0.3767
		Variance Equation		
C(4)	-0.392863	0.013456	-29.19641	0.0000
C(5)	0.262525	0.014683	17.87957	0.0000
C(6)	-0.108192	0.008152	-13.27109	0.0000
C(7)	0.975112	0.001652	590.2001	0.0000

Outcomes of the EGARCH model demonstrate that the term, C, is not statistically significant in the mean. The variance equation describes that the C(4), C(5), and C(6) terms are statistically significant which imply that past volatility of stock indices are significantly, influencing current volatility. The EGARCH variance equation also signifies that there exists the asymmetric behavior in volatility which means that positive shocks are effecting, differently, than the negative on volatility.

4.4 PARCH Model

Table 9. Output of PARCH model on DSE20 index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.77E-05	0.000234	0.075571	0.9398
		Variance Equation		
C(4)	2.90E-05	1.17E-05	2.479037	0.0132
C(5)	0.146467	0.010642	13.76328	0.0000
C(6)	-0.087325	0.025857	-3.377242	0.0007
C(7)	0.868686	0.008261	105.1538	0.0000
C(8)	1.503084	0.091508	16.42574	0.0000

Table 10. Output of PARCH model on DSE general index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.037258	2154.827	0.000481	0.9996
		Variance Equation		
C(4)	2.59E-10	2.96E-10	0.874029	0.3821
C(5)	0.336848	0.017051	19.75544	0.0000
C(6)	0.189525	0.017781	10.65881	0.0000
C(7)	0.687310	0.016965	40.51252	0.0000
C(8)	3.796199	0.245353	15.47240	0.0000

Outputs of the PARCH model show that the term, C, is not statistically significant in the mean equation. The variance equation describes that the terms, C(4), C(5), C(6), C(7), and C(7) are statistically significant which imply that past volatility of DSE20 and DSE general indices are significantly, influencing current volatility.

4.5 TARCH Model

Table 11. Output of TARCH model on DSE20 index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	8.77E-05	0.000234	0.374501	0.7080
	Variance Equation			
C	3.71E-06	2.64E-07	14.05148	0.0000
RESID(-1)^2	0.177662	0.014529	12.22848	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.038735	0.014203	-2.727274	0.0064
GARCH(-1)	0.841909	0.008403	100.1911	0.0000

Table 12. Output of TARCH model on DSE general index

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000419	0.000729	0.574428	0.5657
	Variance Equation			
C	2.09E-06	3.67E-07	5.691682	0.0000
RESID(-1)^2	0.141486	0.010535	13.42948	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.295546	0.026135	11.30847	0.0000
GARCH(-1)	0.804898	0.003769	213.5778	0.0000

Results of the TARCH model represent that the terms, C, are not statistically significant in both the mean as well as variance equations. The variance equation describes that the RESID(-1)^2, RESID(-1)^2*(RESID(-1)<0), and GARCH(-1) terms are statistically significant which imply that past volatility of DSE20 and DSE general indices are significantly, influencing current volatility.

4.6 Statistical Performance

4.6.1 In-Sample Statistical Performance

The following table presents the comparison of the in-sample statistical performance results of the selected models.

Table 13. In -sample statistical performance results on DSE20 index returns

Particulars	Model				
	GARCH	EGARCH	ARCH	PARCH	TARCH
Mean Absolute Error	0.0075	0.0075	0.0075	0.0075	0.0075
Mean Absolute Percentage Error	157.37%	149.10%	209.63%	149.15%	145.60%
Root Mean Squared Error	0.0108	0.0108	0.0108	0.0108	0.0108
Theil's Inequality Coefficient	0.8347	0.8406	0.8239	0.8427	0.8350

Table 13 reveals that all models have the same and the lowest MAE and RMSE at 0.0075 and 0.0108 respectively. PARCH model has the lowest MAPE at 67.43%, whereas ARCH model has the lowest theil's inequality coefficient at 0.8239. Therefore, both the ARCH and PARCH models are nominated as the best model once, while the GARCH, EGARCH, and TARCH models are nominated not a single time in case of DSE20 index returns series.

Table 14. In -sample statistical performance results on DSE general index returns

Particulars	Model				
	GARCH	EGARCH	ARCH	PARCH	TARCH
Mean Absolute Error	0.0075	0.0075	0.0074	0.0075	0.0075
Mean Absolute Percentage Error	259.73%	279.44%	176.57%	213.62%	249.77%
Root Mean Squared Error	0.0106	0.0107	0.0105	0.0106	0.0106
Theil's Inequality Coefficient	0.8118	0.7984	0.8713	0.8482	0.8185

Table 14 demonstrates that both all models have the same and lowest MAE at 0.0074., whereas AR has the lowest MAPE at 67.43%. ARCH model has the lowest MAPE and RMSE 176.57% and at 0.0105, whereas the EGARCH model has the lowest theil's inequality coefficient at 0.7984. Therefore, the best is the ARCH model in case of DSE general index returns series.

4.6.2 Out – Of- Sample Statistical Performance

Table 15. Out –of - sample statistical performance result on DSE20 index returns

Particulars	Model				
	GARCH	EGARCH	ARCH	PARCH	TARCH
Mean Absolute Error	0.0109	0.0109	0.0109	0.0109	0.0109
Mean Absolute Percentage Error	146.33%	143.45%	150.19%	142.64%	146.27%
Root Mean Squared Error	0.0172	0.0171	0.0172	0.0172	0.0172
Theil's Inequality Coefficient	0.8548	0.8611	0.8499	0.8617	0.8551

Table 15 illustrates that all models have the same and the lowest MAE at 0.0109. PARCH model has the lowest MAPE at 142.64%, EGARCH model has the lowest RMSE at 0.0171 and ARCH model has the lowest theil's inequality coefficient at 0.8499. So, it can be mentioned that all models except GARCH and TARCH models are nominated as the best model once in case of DSE20 index return series.

Table 16. Out –of - sample statistical performance result on DSE general index returns

Particulars	Model				
	GARCH	EGARCH	ARCH	PARCH	TARCH
Mean Absolute Error	0.0125	0.0123	0.0124	0.0121	0.0122
Mean Absolute Percentage Error	409.37%	374.71%	279.46%	283.78%	329.03%
Root Mean Squared Error	0.0205	0.0208	0.0208	0.0206	0.0207
Theil's Inequality Coefficient	0.8608	0.8436	0.8898	0.8874	0.8609

Table 16 discloses that the PARCH and ARCH models have the lowest MAE and MAPE at 0.0121 and 279.46% respectively, whereas the GARCH and EGARCH models have the minimum RMSE and theil's inequality coefficient at 0.0205 and 0.8436 accordingly. Therefore, it can be states that each model is nominated as the best model once in case of DSE general index return series.

4.7 Trading Performance

4.7.1 In-Sample Trading Performance

Table 17. In- sample trading performance results on DSE20 index returns

Particulars	Model				
	GARCH	EGARCH	ARCH	PARCH	TARCH
Annualised Return	53.11%	53.35%	47.66%	53.57%	**53.59%**
Annualised Volatility	17.11%	17.10%	17.17%	17.10%	17.10%
Sharpe Ratio	3.10	3.12	2.78	3.13	3.13
Maximum Drawdown	-14.63%	-14.63%	-16.25%	-14.63%	-14.63%

Table 17 shows that the TARCH model has the highest annualized return at 39.43%, whereas EGARCH, PARCH, and TARCH models have the same and the lowest annualized volatility at 17.10%. Both the PARCH and TARCH models have the same and highest Sharpe ratio at 3.13. The ARCH model has the minimum downside risk s measured by maximum drawdown at -16.25%. All models except GARCH are selected as the best model once in case of DSE20 index returns series.

Table 18. In- sample trading performance results on DSE general index returns

Particulars	Model				
	GARCH	EGARCH	ARCH	PARCH	TARCH
Annualised Return	25.77%	25.54%	42.14%	25.48%	25.46%
Annualised Volatility	16.76%	16.77%	16.63%	16.77%	16.77%
Sharpe Ratio	1.54	1.52	2.53	1.52	1.52
Maximum Drawdown	-26.75%	-27.72%	-18.75%	-28.22%	-33.15%

Table 18 illustrates that the ARCH model has the highest annualized return as well as Sharpe ratio at 42.14% and 2.53 respectively. On the other hand, ARCH and TARCH models have the lowest annualized volatility and maximum drawdown at 16.63% and 33.15% accordingly. Therefore, ARCH model is the best model in case of DSE general index returns series.

4.7.2 Out-Of-Sample Trading Performance

Table 19. Out-of-sample trading performance results on DSE20 index returns

Particulars	Model				
	GARCH	EGARCH	ARCH	PARCH	TARCH
Annualised Return	47.16%	48.06%	37.89%	48.02%	46.72%
Annualised Volatility	40.21%	40.15%	40.20%	40.21%	40.37%
Sharpe Ratio	1.17	1.20	0.94	1.19	1.16
Maximum Drawdown	-30.57%	-33.40%	-53.35%	-30.57%	-27.45%

Table 19 demonstrates that the EGARCH model has the highest annualized return, lowest annualized volatility, and highest at Sharpe ratio at 48.06%, 40.15%%, and 1.20 respectively. ARCH model has the lowest maximum drawdown at -53.35%. Therefore, the EGARCH model is selected as the best performing model DSE20 index returns series.

Table 20. Out-of-sample trading performance results on DSE general index returns

Particulars	Model				
	GARCH	EGARCH	ARCH	PARCH	TARCH
Annualised Return	40.64%	27.62%	32.55%	30.10%	26.38%
Annualised Volatility	42.13%	42.15%	41.63%	42.11%	42.14%
Sharpe Ratio	0.96	0.66	0.78	0.71	0.63
Maximum Drawdown	-32.72%	-55.63%	-61.02%	-48.48%	-56.44%

Table 20 shows that the GARCH model has the highest annualized return, and Sharpe ratio at 40.64% and 0.96 respectively. On the other hand, ARCH model has the lowest annualized volatility and maximum drawdown at 41.63% and -61.02% accordingly. Therefore, the GARCH ARCH models are nominated as the best performing model twice, whereas other models are not nominated single time in case of DSE20 index returns series.

5. Conclusion

In this study, ARCH model is used to forecast volatility of the stock indices, namely DSE20 index and DSE general index. GARCH, EGARCH, PARCH, and TARCH models are applied as benchmark models for the study purpose. The daily data from December 1, 2001 to September 10, 2011 is used in this study out of which, in-sample data set covers from December 1, 2001 to August 14, 2008 and, whereas out-of-sample covers from August 18, 2008 to September 10. The results of ARCH models on both the DSE20 and DSE general indices series show that in the variance equation the terms, C and RESID(-1)^2 are statistically significant which imply that the volatility of risk is influenced by past square residual terms. The outcomes of the GARCH model on the selected stock indices returns also demonstrate that the RESID(-1)^2 term is statistically significant which imply that the volatility of risk is influenced by past square residual terms. The GARCH (-1) term is also statistically significant for the both indices. Outputs of EGARCH model on the sample stock indices show that the C(4), C(5), and C(6) terms are statistically significant which imply that past volatility of stock indices are significantly, influenced current volatility. Therefore, the EGARCH variance equation demonstrates that the asymmetric behavior are existed in volatility which means that positive shocks are affected, differently, than the negative shocks on volatility. The outputs of PARCH model on the selected stock indices returns series demonstrate that the terms, C(4), C(5), C(6), C(7), and C(7) are statistically significant which imply that past volatility of DSE20 and DSE general indices returns series are significantly, influenced present volatility. In addition, the results of TARCH model on the sample stock indices illustrate that in the variance equation the RESID(-1)^2, RESID(-1)^2*(RESID(-1)<0), and GARCH(-1) terms are statistically significant which mean that past volatility of DSE20 and DSE general indices returns series are significantly, influenced current volatility.

The results of the in-sample statistical performance show that both the ARCH and PARCH models are selected as the best performing model jointly for DSE20 index returns, whereas for DSE general index returns series, ARCH model outperforms other models. Outcomes of the out – of- sample statistical performance demonstrate that all models except GARCH and TARCH models are considered as the best model jointly in case of DSE20 index returns series, while each model is nominated as the best model once for DSE general index returns series. The outcomes of the in-sample trading performance illustrate that all models except GARCH are selected as the best model jointly for DSE20 index returns series, while ARCH model is selected as the best model for DSE general index returns series. Moreover, based on the outputs of out-of-sample trading performance, the EGARCH model is the best performing model for DSE20 index returns series, whereas the GARCH and ARCH models are selected as the best performing model jointly for DSE general index returns series.

References

Al-Zeaud, H. A. (2011). Modelling and forecasting volatility using ARIMA model. *European Journal of Economics, Finance and Administrative Sciences*, *35,* 109-125.

Bollerslev, T. P. (1986). Generalized autoregressive conditional heteroscedasticity. *J. Econ*., *31*, 307-327.

Brooks, C. (2008). *Introductory econometrics for finance* (2nd ed.). Cambridge: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511841644

Chang, J-F., Wei, L-Y., & Cheng, C-H. (2009). ANFIS-based adaptive expectation model for forecasting stock index. *International Journal of Innovative Computing, Information and Control*, *5*(7), 1949-1958.

Chen, T-L. (2011). Forecasting the Taiwan stock market with a stock trend recognition model based on the characteristic matrix of a bull market. *African Journal of Business Management*, *5*(23), 9947-9960. http://dx.doi.org/10.5897/AJBM11.1173

Dunis, C. L., Laws, J., & Karathanasopoulos, A. (2011). Modelling and trading the Greek stock Market with mixed neural network models. *Working Paper Series No. 15,* Centre for EMEA Banking, Finance & Economics, London Metropolitan Business School.

Ederington, L. H., & Guan, W. (2005). Forecasting Volatility. *Journal of Futures Markets, 25*(5), 465–490. http://dx.doi.org/10.1002/fut.20146

Glosten, L. R. et al. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *J. Finance*, *48*, 1779-1801. http://dx.doi.org/10.1111/j.1540-6261.1993.tb05128.x

Gupta, A., & Dhingra, B. (n.d.). Stock market prediction using hidden markov models. Retrieved from http://home.iitk.ac.in/~gaditya/Submissions/PID2221657.pdf

Islam, M., Ali, L. E., & Afroz, N. (2012). Forecasting volatility of Dhaka Stock Exchange: Linear vs non-linear models. *Internat. J. of Sci. and Eng., 3*(2), 4-8.

Lee, K. J., Chi, A. Y., Yoo, S., & Jin, J. J. (2008). Forecasting korean stock price index (kospi) using back propagation neural network model, bayesian chiao's model, and sarima model. *Academy of Information and Management Sciences Journal, 11*(2), 53-56.

Leung, M. T., Daouk, H., & Chen, A-S. (2000). Forecasting stock indices: a comparison of classification and level estimation models. *International Journal of Forecasting, 16*, 173–190. http://dx.doi.org/10.1016/S0169-2070(99)00048-5

Louzis, D. P., Xanthopoulos-Sisinis, S., & Refenes, A. P. (2010). Stock index realized volatility forecasting in the presence of heterogeneous leverage effects and long range dependence in the volatility of realized volatility. *International Conference on Applied Economics – ICOA*E, 465-478.

Mcmillan, D., Speigh, Alan, T., & Apgwilym, O. (2000). Forecasting UK stock market volatility. *Applied Financial Economics*, *10*, 435–448. http://dx.doi.org/10.1080/09603100050031561

Mehrara, M., Moeini, A., Ahrari, M., & Ghafari, A. (2010). Using technical analysis with neural network for forecasting stock price index in Tehran stock exchange. *Middle Eastern Finance and Economics*, *6*, 50-61.

Nelson, D. (1991). Conditional heteroscedasticity in asset returns: A new approach. *Econ*., *59*(2), 347-370. http://dx.doi.org/10.2307/2938260

Panait, I., & Slăvescu, F. O. (2012). Using GARCH-in-mean model to investigate volatility and persistence at different frequencies for Bucharest Stock Exchange during 1997 - 2012. *Theoretical and Applied Economics, 19*(5), 55-76.

Sutheebanjard, P., & Premchaiswadi, W. (2010). Forecasting the Thailand stock market using evolution strategies. *Asian Academy of Management Journal of Accounting and Finance*, *6*(2), 85–114.

Tang, X., Yang, C., & Zhou, J. (2009). Stock price forecasting by combining news mining and time series analysis. *International Joint Conference on Web Intelligence and Intelligent Agent Technology- Workshop*, 279-283.

Taylor, S. (1986). *Modelling financial time series.* New York: John Wiley and Sons.

Torben, D., Doberv,D., & Schaumbury, E. (2009). Jump-robust volatility estimation using nearest neighbor truncation. *NBER, Working Paper*, 15533.

Wang, J. L., & Chan S. H. (2007). Stock market trading rule discovery using pattern recognition and technical analysis. *Expert. Syst. Appl*., *33*, 304-315. http://dx.doi.org/10.1016/j.eswa.2006.05.002

Yalama, A., & Sevil, G. (2008). Forecasting world stock markets volatility. *International Research Journal of Finance and Economics*, *15*, 159-174.

Zakoïan, J. M. (1994). Threshold heteroskedasticmodels. *J. Econ. Dynam. Cont. Elsevier*, *18*(5), 931-955. http://dx.doi.org/10.1016/0165-1889(94)90039-6

Appendices

A1. ARCH

Dependent Variable: RDSE20INDX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/09/12 Time: 20:56
Sample (adjusted): 2 2600
Included observations: 2599 after adjustments
Convergence achieved after 151 iterations
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000588	0.000327	1.796475	0.0724
AR(1)	0.028313	0.088584	0.319613	0.7493
MA(1)	0.165004	0.088777	1.858632	0.0631
		Variance Equation		
C	0.000136	6.30E-07	216.3510	0.0000

RESID(-1)^2	0.222378	0.020218	10.99896	0.0000

R-squared	-0.010388	Mean dependent var	0.000521
Adjusted R-squared	-0.011166	S.D. dependent var	0.013207
S.E. of regression	0.013280	Akaike info criterion	-5.892177
Sum squared resid	0.457858	Schwarz criterion	-5.880898
Log likelihood	7661.884	Hannan-Quinn criter.	-5.888090
Durbin-Watson stat	2.247959		

Inverted AR Roots	.03
Inverted MA Roots	-.17

Dependent Variable: RDSEGENRINDX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/09/12 Time: 21:17
Sample (adjusted): 2 2600
Included observations: 2599 after adjustments
Convergence achieved after 197 iterations
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000293	0.000259	1.131417	0.2579
AR(1)	-0.053025	0.123946	-0.427804	0.6688
MA(1)	0.187110	0.124267	1.505705	0.1321
Variance Equation				
C	0.000157	9.64E-07	163.0593	0.0000
RESID(-1)^2	0.345453	0.025560	13.51550	0.0000

R-squared	-0.012838	Mean dependent var	0.000753
Adjusted R-squared	-0.013618	S.D. dependent var	0.014654
S.E. of regression	0.014753	Akaike info criterion	-5.692243
Sum squared resid	0.565060	Schwarz criterion	-5.680964
Log likelihood	7402.070	Hannan-Quinn criter.	-5.688157
Durbin-Watson stat	2.219778		

Inverted AR Roots	-.05
Inverted MA Roots	-.19

A2. GARCH

Dependent Variable: RDSE20INDX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/09/12 Time: 20:33
Sample (adjusted): 2 2600
Included observations: 2599 after adjustments
Convergence achieved after 64 iterations
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.59E-05	0.000211	-0.075233	0.9400
AR(1)	-0.161766	0.115991	-1.394641	0.1631
MA(1)	0.344312	0.113062	3.045346	0.0023
Variance Equation				
C	3.97E-06	2.57E-07	15.45235	0.0000
RESID(-1)^2	0.158877	0.011755	13.51586	0.0000
GARCH(-1)	0.840005	0.008207	102.3540	0.0000

R-squared	-0.014306	Mean dependent var	0.000521
Adjusted R-squared	-0.015087	S.D. dependent var	0.013207
S.E. of regression	0.013306	Akaike info criterion	-6.121655
Sum squared resid	0.459634	Schwarz criterion	-6.108120
Log likelihood	7961.090	Hannan-Quinn criter.	-6.116751
Durbin-Watson stat	2.233730		

Inverted AR Roots	-.16
Inverted MA Roots	-.34

Dependent Variable: RDSEGENRINDX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/09/12 Time: 21:04
Sample (adjusted): 2 2600
Included observations: 2599 after adjustments
Convergence achieved after 458 iterations
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.764238	2757.931	0.001727	0.9986
AR(1)	0.999994	0.003262	306.5575	0.0000
MA(1)	-0.970049	0.006777	-143.1339	0.0000
Variance Equation				
C	1.76E-06	3.60E-07	4.881778	0.0000
RESID(-1)^2	0.318826	0.015093	21.12347	0.0000
GARCH(-1)	0.794913	0.004796	165.7431	0.0000

R-squared	-0.010924	Mean dependent var	0.000753
Adjusted R-squared	-0.011703	S.D. dependent var	0.014654
S.E. of regression	0.014740	Akaike info criterion	-5.910645
Sum squared resid	0.563992	Schwarz criterion	-5.897110
Log likelihood	7686.883	Hannan-Quinn criter.	-5.905741
Durbin-Watson stat	1.986440		

Inverted AR Roots	1.00
Inverted MA Roots	.97

A3. EGARCH

Dependent Variable: RDSE20INDX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/09/12 Time: 20:39
Sample (adjusted): 2 2600
Included observations: 2599 after adjustments
Convergence achieved after 130 iterations
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.74E-05	0.000240	0.239442	0.8108
AR(1)	-0.068093	0.117469	-0.579664	0.5621
MA(1)	0.243882	0.115365	2.114002	0.0345
		Variance Equation		
C(4)	-0.346061	0.027068	-12.78504	0.0000
C(5)	0.216456	0.015061	14.37157	0.0000
C(6)	0.029801	0.007039	4.233534	0.0000
C(7)	0.978565	0.002021	484.2629	0.0000

R-squared	-0.008993	Mean dependent var	0.000521
Adjusted R-squared	-0.009771	S.D. dependent var	0.013207
S.E. of regression	0.013271	Akaike info criterion	-6.116116
Sum squared resid	0.457226	Schwarz criterion	-6.100325
Log likelihood	7954.892	Hannan-Quinn criter.	-6.110394
Durbin-Watson stat	2.213886		

Inverted AR Roots	-.07
Inverted MA Roots	-.24

Dependent Variable: RDSEGENRINDX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/09/12 Time: 21:12
Sample (adjusted): 2 2600
Included observations: 2599 after adjustments
Convergence achieved after 410 iterations
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000366	0.000414	0.884059	0.3767
AR(1)	1.012952	0.002394	423.0446	0.0000
MA(1)	-0.975389	0.003824	-255.0493	0.0000
		Variance Equation		

C(4)	-0.392863	0.013456	-29.19641	0.0000
C(5)	0.262525	0.014683	17.87957	0.0000
C(6)	-0.108192	0.008152	-13.27109	0.0000
C(7)	0.975112	0.001652	590.2001	0.0000

R-squared	-0.023747	Mean dependent var	0.000753
Adjusted R-squared	-0.024535	S.D. dependent var	0.014654
S.E. of regression	0.014833	Akaike info criterion	-5.917634
Sum squared resid	0.571146	Schwarz criterion	-5.901843
Log likelihood	7696.965	Hannan-Quinn criter.	-5.911912
Durbin-Watson stat	1.976562		

Inverted AR Roots 1.01

Estimated AR process is nonstationary

Inverted MA Roots .98

A4. PARCH

Dependent Variable: RDSE20INDX

Method: ML - ARCH (Marquardt) - Normal distribution

Date: 11/09/12 Time: 20:42

Sample (adjusted): 2 2600

Included observations: 2599 after adjustments

Convergence achieved after 54 iterations

MA Backcast: 1

Presample variance: backcast (parameter = 0.7)

@SQRT(GARCH)^C(8) = C(4) + C(5)*(ABS(RESID(-1)) - C(6)*RESID(
-1))^C(8) + C(7)*@SQRT(GARCH(-1))^C(8)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.77E-05	0.000234	0.075571	0.9398
AR(1)	-0.161234	0.122965	-1.311217	0.1898
MA(1)	0.332514	0.119330	2.786499	0.0053
Variance Equation				
C(4)	2.90E-05	1.17E-05	2.479037	0.0132
C(5)	0.146467	0.010642	13.76328	0.0000
C(6)	-0.087325	0.025857	-3.377242	0.0007
C(7)	0.868686	0.008261	105.1538	0.0000
C(8)	1.503084	0.091508	16.42574	0.0000

R-squared	-0.010846	Mean dependent var	0.000521
Adjusted R-squared	-0.011625	S.D. dependent var	0.013207
S.E. of regression	0.013283	Akaike info criterion	-6.123853
Sum squared resid	0.458066	Schwarz criterion	-6.105807
Log likelihood	7965.948	Hannan-Quinn criter.	-6.117315
Durbin-Watson stat	2.208889		

Inverted AR Roots -.16

Inverted MA Roots -.33

Dependent Variable: RDSEGENRINDX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/09/12 Time: 21:14
Sample (adjusted): 2 2600
Included observations: 2599 after adjustments
Convergence achieved after 214 iterations
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(8) = C(4) + C(5)*(ABS(RESID(-1)) - C(6)*RESID(
-1))^C(8) + C(7)*@SQRT(GARCH(-1))^C(8)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.037258	2154.827	0.000481	0.9996
AR(1)	0.999999	0.002402	416.2704	0.0000
MA(1)	-0.976723	0.004733	-206.3862	0.0000
		Variance Equation		
C(4)	2.59E-10	2.96E-10	0.874029	0.3821
C(5)	0.336848	0.017051	19.75544	0.0000
C(6)	0.189525	0.017781	10.65881	0.0000
C(7)	0.687310	0.016965	40.51252	0.0000
C(8)	3.796199	0.245353	15.47240	0.0000

R-squared	-0.004575	Mean dependent var	0.000753
Adjusted R-squared	-0.005349	S.D. dependent var	0.014654
S.E. of regression	0.014693	Akaike info criterion	-5.965368
Sum squared resid	0.560450	Schwarz criterion	-5.947322
Log likelihood	7759.996	Hannan-Quinn criter.	-5.958830
Durbin-Watson stat	1.985711		

Inverted AR Roots	1.00
Inverted MA Roots	.98

A5. TARCH

Dependent Variable: RDSE20INDX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/09/12 Time: 21:08
Sample (adjusted): 2 2600
Included observations: 2599 after adjustments
Convergence achieved after 67 iterations
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) +
C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	8.77E-05	0.000234	0.374501	0.7080
AR(1)	-0.167992	0.115972	-1.448556	0.1475
MA(1)	0.349225	0.112577	3.102112	0.0019

Variance Equation

C	3.71E-06	2.64E-07	14.05148	0.0000
RESID(-1)^2	0.177662	0.014529	12.22848	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.038735	0.014203	-2.727274	0.0064
GARCH(-1)	0.841909	0.008403	100.1911	0.0000

R-squared	-0.013728	Mean dependent var	0.000521
Adjusted R-squared	-0.014509	S.D. dependent var	0.013207
S.E. of regression	0.013302	Akaike info criterion	-6.122082
Sum squared resid	0.459372	Schwarz criterion	-6.106291
Log likelihood	7962.645	Hannan-Quinn criter.	-6.116360
Durbin-Watson stat	2.232191		

Inverted AR Roots	-.17
Inverted MA Roots	-.35

Dependent Variable: RDSEGENRINDX
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 11/09/12 Time: 21:10
Sample (adjusted): 2 2600
Included observations: 2599 after adjustments
Convergence achieved after 203 iterations
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) +
C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000419	0.000729	0.574428	0.5657
AR(1)	1.007135	0.002502	402.4537	0.0000
MA(1)	-0.974009	0.004420	-220.3406	0.0000

Variance Equation

C	2.09E-06	3.67E-07	5.691682	0.0000
RESID(-1)^2	0.141486	0.010535	13.42948	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.295546	0.026135	11.30847	0.0000
GARCH(-1)	0.804898	0.003769	213.5778	0.0000

R-squared	-0.014434	Mean dependent var	0.000753
Adjusted R-squared	-0.015215	S.D. dependent var	0.014654
S.E. of regression	0.014765	Akaike info criterion	-5.954373
Sum squared resid	0.565950	Schwarz criterion	-5.938582
Log likelihood	7744.707	Hannan-Quinn criter.	-5.948651
Durbin-Watson stat	1.985876		

Inverted AR Roots	1.01
	Estimated AR process is nonstationary
Inverted MA Roots	.97