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Modeling and Forecasting of Return Volatility in Bangladeshi Stock Markets under GARCH Framework

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Abstract

This paper attempted to seek evidence of volatility pattern of daily return of two Bangladeshi stock exchanges (DSE and CSE). To capture volatility dynamics in return series, we applied GARCH, EGARCH, TGARCH and PARCH models. The results suggested that lagged error and lagged variance had significant impact on volatility. Beside this volatility clustering, effect of old news and significant leverage impact were prevailed in both stock markets. It was also found that sock to the conditional variance was highly persistent and took time to dry out. As per log likelihood statistics and AIC, TGARCH model was found to be more attractive to represent daily return data in the sense of volatility dynamics as well as forecasting future volatility.

Keywords: Volatility, GARCH, EGARCH, TGARCH, PARCH, DSE and CSE.

AMS Classification: 62M10.

1. Introduction

Capital market has been worked as the major vehicle of economic growth in both emerging and developed economies, e.g., Dhaka Stock Exchange (DSE) and Chittagong Stock Exchange (CSE) in Bangladesh. As a developing economy, Bangladesh has witness an extreme modification in the financial market (both capital market as well as money market) in the last two decades. Capital market has been playing a pivotal role in the mobilization and allocation of economic resources into the productive activities of the economy. This allocation takes place through the appropriate pricing of securities traded in the stock markets. The investors need to be motivated by saving and investing in the capital market of a country and it is possible if the securities are appropriately priced in the market. Also, foreign Investors have shown an acute interest in Bangladesh stock market that consequence Bangladesh flourishing enough to entice a major segment from foreign investors in recent period. This has increased the risk and volatility with connected investment in financial securities.

Volatility can be defined in simple terms as the frequency and severity of the fluctuations in the market price that is studied by many authors (Oseni and Nwosa, 2011; Alexander, 1999; Ahmed and Suliman, 2011; Mandelbrot,1963; Baille et al., 1996; Chou, 1988; Schwert, 1989; Fama, 1965; Black, 1976; Nelson,1991; Engle and Ng,1993 and so on). All of them addressed the various causes of volatility.

Robert F. Engle (1982) was the first to initiate the concept of conditional heteroscedasticity. He projected a model where the conditional time series is a function of past shocks. This model led to a breakthrough in financial econometrics. The impact this model has had on the research around time-varying volatility gave him the Nobel Prize in Economic Sciences in 2003. Other methods of modeling and forecasting financial volatility such as the Generalized ARCH model proposed by Bollerslev (1986).His generalized autoregressive conditional heteroscedasticity (GARCH) model allows for past conditional variances in the current conditional variance equation. Though the GARCH was based on ARCH model but it has some advantages compared to its predecessor. It is well known that financial returns are often characterized by a number of typical 'stylized facts' such as volatility clustering, studying long-run relationship among time series data, persistence and time variation of volatility. During the past twenty years, GARCH model has been developed into a class of models. Those models have been applied to stock markets, foreign exchange markets and future markets and they are proven to be relatively accurate and easy to use. The existing literature has long since recognized that the distribution of returns can be skewed. For instance, for some stock market indices, returns are skewed toward the left, indicating that there are more negative than positive outlying observations. The intrinsically symmetric distribution such as normal, student-t or Generalized Error

Distribution (GED) cannot cope with such skewness. Consequently, one can expect that forecasts and forecast error variances from a GARCH model may be biased for skewed financial time series.

A lot of empirical studies have been conducted on modeling and forecasting stock market volatility by using ARCH and GARCH specifications and their extensions(Sulin et al.; 2007; French et,al., 1987; Henry, 1998; ; McMillan et al., 2000; ; Poshakwale and Murinde, 2001; GengJia, 2006;; Mala & Raddy, 2007; Srivastava, 2008;Alberg etal., 2008;Fuertes et al., 2009; Liu et al., 2009; Kalu O, 2010; Liu and Hung, 2010; Aal and Ahmed, 2011; Diamandis et al., 2011; Ou and Wang, 2011; Yin et al., 2011;Ahmed and Suliman, 2011;Babikir et al., 2012Gabriel, 2012; Liu et al., 2012; Imam and Amin, 2004; Chowdhury and Iqbal, 2005;Basher et al., 2007;Alam et al., 2007;Uddin and Alam, 2007; Mobarek et al., 2008;Hassan and Chowdhury, 2008; Rahman and Moazzem, 2011; Hossain and Uddin, 2011; Alam et al., 2011 Hasan et al., 2012; Siddikee and Begum, 2016; and so on). Very few of the above authors used ARCH, GARCH-M, GARCH (p, q) and GARCH (1, 1) models with a view of finding the relationship between risks and return relationship of DSE. These researchers have identified the negative relationship between risk and return of DSE from the past statistics which indicates the fact that theory of risk-return relationship does not appear in DSE which is a vital contradictory point. In addition, Aziz and Uddin (2015) provide evidence that 2010 is the peak in terms of volatility in DSE and that volatility is declining overtime using GARCH (1, 1) model.

There is a little literature on stock market volatility analysis in Bangladesh, and very few studies have focused on GARCH type models. Still, as far our knowledge, no body has conducted their work to make comparison between DSE and CSE in aspect of modeling volatility as well as forecasting ability of models. Motivated by these empirical studies, this paper examines volatility of stock return of the Bangladesh stock markets (DSE and CSE) by GARCH type models and testing the models' forecasting ability with accuracy.

2. Materials and Methodology

The study is based on secondary data. The daily closing values of both DSEX and CSCX have been taken from the DSE and CSE website over a period of four years from January 28, 2013 to December 29, 2016.

As for the analysis purpose, the stock index is converted into stock index return to avoid complications following the algorithm expressing the difference in the logarithm between the yield of closing price of today and of yesterday's as

$$r_t = \ln(y_t) - \ln(y_{t-1}) \tag{1}$$

where, r_t denotes t day's rate of return, y_t denotes today's closing price, and y_{t-1} denotes yesterday's closing price.

Various statistical tools, ARCH-LM test, Augmented Dicker Fuller (ADF) test, Phillips-Perron test, are used in the study. An Autoregressive Moving Average (ARMA) model is assumed for the error variance; the model is a generalized autoregressive conditional heteroskedasticity (GARCH) Bollerslev (1986) model, which generalizes the ARCH(q) model to GARCH(p, q) model. Liu and Hung (2010), Ou and Wang (2011), and Yin et al. (2011) have used ARCH and GARCH models to measure volatility. Descriptive statistics provides simple summaries about the sample and about the observations that have been made. Likewise, unit root test is done to check the data stationarity as time series data are involve.

GARCH model:

Traditional econometric models assume a constant one-period forecast variance. To generalize this implausible assumption, Robert Engle presented a class of processes called autoregressive conditional heteroscedasticity (ARCH). These are zero mean, serially uncorrelated processes with non-constant variance conditional on the past. A useful generalization of this model is the GARCH parameterization introduced by Bollerslev (1986). This model is also a weighted average of past squared residuals, but it has declining weights that never go completely to zero. Below is the original GARCH model:

Mean Equation: $r_t = x'_t b + \varepsilon_t; \quad \varepsilon_t \sim N(0, \sigma^2)$ (2)

Variance Equation: $h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}$ (3)

Because GARCH(p,q) is an extension of ARCH model, it has all the characteristics of the original ARCH model. And because in GARCH model the conditional variance is not only the linear function of the square of the lagged residuals, it is also a linear 4 function of the lagged conditional variances, GARCH model is more accurate than the original ARCH model and it is easier to calculate.

The most widely used GARCH model is GARCH(1,1) model. The (1,1) in parentheses is a standard notation in which the first number refers to how many autoregressive lags, or ARCH terms, appear in the equation, while the second number refers to how many moving average lags are specified, which here is often called the number of GARCH terms. Sometimes models with more than one lag are needed to find good variance forecasts. GARCH(1,1) is the most widely used GARCH model because it is accuracy and simplicity.

Although GARCH model is very useful in the forecasting of volatility and asset pricing, there are still several problems GARCH model cannot explain. The biggest problem is that standard GARCH models assume that positive and negative error terms have a symmetric effect on the volatility. In other words, good and bad news have the same effects on the volatility in this model. In practice this assumption is frequently violated, in particular by stock returns, in that the volatility increases more after bad news than after good news.

According to the problems in the standard GARCH model, a number of parameterized extensions of the standard GARCH model have been suggested recently. In the following I will discuss two of the most important ones: the exponential GARCH (EGARCH) model and GARCH-M model.

EGARCH model:

Exponential GARCH (EGARCH) model was first presented by Nelson in 1991. The main purpose of EGARCH model is to describe the asymmetrical response of the market under the positive and negative shocks. In EGARCH model, we have

$$\ln(h_t) = \alpha_0 + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{p} \beta_j \ln\left(h_{t-j}\right) \tag{4}$$

where

$$g(z_t) = \theta z_t + \beta[|z_t| - E|z_t|]$$

$$z_t = \varepsilon_t \Big/ \sqrt{h_t}$$

We can see in equation (4), the Nelson rewrote the conditional variance with the natural log of the conditional variance. When $\theta \neq 0$, the effects of information are asymmetry. When,$\theta < 0$ there is a significant leverage effect. If we compared the above equations with the definition of the original GARCH mode, we can see that there are no constraints for the parameters. This is one of the biggest advantages of EGARCH model compared to the standard GARCH model.

TGARCH model:

Threshold ARCH (TARCH) model was first presented by Zakoian in 1990. It has the following conditional variance:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{5}$$

Where d_t is latent variable

$$d_t = \begin{cases} 1 & \varepsilon_t < 0 \\ 0 & \varepsilon_t \geq 0 \end{cases}$$

Because d_t is included, the increase ($\varepsilon_t < 0$) and decrease ($\varepsilon_t > 0$) of stock prices will have different effects on conditional variance. When the stock prices increase, $\gamma \varepsilon_{t-1}^2 d_{t-1} = 0$ the effects can be described by the parameter $\sum_{i=1}^{q} \alpha_i$; when the prices decrease, the effects can be described by the parameter $\sum_{i=1}^{q} \alpha_i + \gamma$. If $\gamma \neq 0$ we conclude that the information has asymmetrical effects. If $\gamma > 0$ we say that there is leverage effect.

PARCH Model:

Taylor (1986) and Schwert (1989) introduced the standard deviation GARCH model, where the standard deviation is modelled rather than the variance. This model, along with several other models, is generalized in Ding et al. (1993) with the Power ARCH specification. In the Power ARCH model, the power parameter δ of the standard deviation can be estimated rather than imposed, and the optional γ parameters are added to capture asymmetry of up to order r:

$$h_t^{\delta} = \alpha_0 + \sum_{i=1}^{q} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{p} \beta_j h_{t-j}^{\delta} \tag{6}$$

where $\delta > 0$. $|\gamma_i| \leq 1$for i =1, 2, …, r, $\gamma_i = 0$ for i > r, and r ≤ p.

The symmetric model sets $\gamma_i = 0$ for all i. If $\delta = 2$ and $\gamma_i = 0$ for all I, the PARCH model is simply a standard GARCH specification and the asymmetric effects are present if $\gamma \neq 0$.

3. Result and Discussions

The sample data were taken from DSE and CSE and each consist of T= 851 observations. In order to have a standard for the results, the study related trading in these shares to daily market indices representing more mature stock markets, including indices of the DSE and CSE. From the time series graph in Figure 1, the pattern of returns for Dhaka Stock Exchange (DSE) and Chittagong Stock

Exchange (CSE), we can observe that large positive change followed by a large negative change and small positive change followed by small change and vice-versa. This indicates both time series have significant time varying variances and it's also a strong indication of volatility clustering. Besides, it is suitable to place conditional variance into the function to describe the effects of risk on the returns and therefore, we should apply GARCH family model in this study.

DSEX CSCX

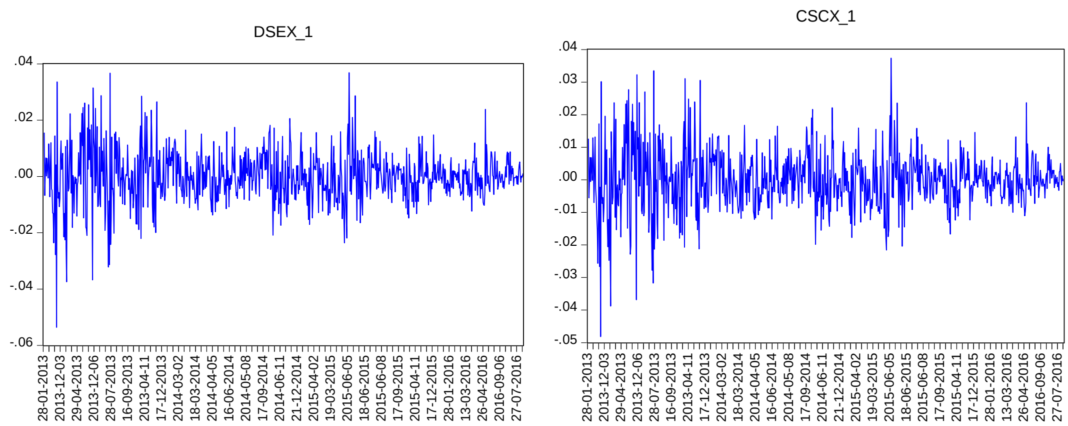

Figure 1: Time-series graph for returns in Dhaka Stock Exchange (DSE) and Chittagong Stock Exchange(CSE)

The result in Table 1 presents basic statistics and normality test. The value of skewness and kurtosis indicating that the two stock market returns were not symmetrically distributed and their nature were leptokurtic referring that stock market return volatility exist in both exchanges. From normality test both DSE and CSE indices do not follow normal distribution in the long run.

Table 1: Descriptive Statistics of returns of DSE and CSE

	Mean	Max	Min	SD	Skewness	Kurtosis	JB test	P value	Observation
DSEX	0.000131	0.036847	-0.05358	0.009224	-0.08424	5.922266	303.8078	0.000	851
CSCX	5.82E-05	0.037332	-0.04813	0.009122	0.012808	5.572938	234.7578	0.000	851

Table 2 represents the results of unit root tests and ARCH-LM test. We observe that the ADF and PP tests reject null hypothesis (Ho: series contains unit root) for both return series at 1% level of significance. We can conclude that both the return series are stationary and suitable for applying econometric tools. On the other hand, the value of ARCH-LM test statistics is very high and significant indicating the series contain ARCH effect. So, due to the presence of ARCH effect in residuals series, now we can proceed for the modeling of return volatility by using GARCH family models.

Table 2: Unit Root Test and ARCH-LM test of DSE and CSE

	Unit Root Test					**ARCH LM test**	
	Augmented Dickey-Fuller test			**Phillips-Perron test**			
	Test Statistic	**p-value**		**Test Statistic**	**p-value**	**Test Statistic**	**p value**
DSEX	-26.8649	0.000		-27.3088	0.000	87.7540	0.000
CSCX	-26.0428	0.000		-26.4485	0.000	81.7883	0.000

Table 3 and Table 4 represent the estimated results of the coefficients of various GARCH models under normal, student's-t and GED distribution for both DSE and CSE. It is found that the estimated value of α (ARCH effect), β (GARCH effect) and γ (Leverage effect) under four models and three distribution are highly significant. The significant α and β indicate that the lagged squared error and lagged conditional variance have a significant impact on volatility in both DSE and CSE. The β coefficient in each conditional variance equation is remarkably larger than α, indicating the old news is more important in market and that has significant impact on future volatility. We have also found that γ coefficients are significant in all cases which confirm that negative shocks (bad news) have a larger effect on conditional variance than the positive shocks (good news) of a same magnitude. Besides, the persistence of conditional variance process is measured by the sum of α and β.

Table 3: Estimates of DSEX using different models

		DSEX											
		GARCH			TGARCH			EGARCH			PARCH		
Parameter		Normal	Student's-t	GED	Normal	Student's-t	GED	Normal	Student's-t	GED	Normal	Student's-t	GED
C	Coeff.	0.00022	0.00016	0.00013	-1.3E-05	-3.4E-05	-4.9E-05	-8.7E-05	-0.00011	-0.00012	-0.00010	-0.00012	-0.00013
	Prob.	(0.3081)	(0.4812)	(0.5437)	(0.9530)	(0.8805)	(0.8261)	(0.6810)	(0.6207)	(0.5588)	(0.6276)	(0.5579)	(0.5351)
AR(1)	Coeff.	0.13316	0.13806	0.13879	0.14572	0.14652	0.14671	0.13581	0.13705	0.13765	0.12989	0.13208	0.13379
	Prob.	(0.0004)	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0003)	(0.0006)	(0.0005)	(0.0003)
C	Coeff.	1.00E-06	1.01E-06	1.02E-06	6.61E-07	6.92E-07	6.98E-07	-0.39054	-0.40341	-0.40483	0.00011	0.00012	0.00012
	Prob.	(0.0605)	(0.0807)	(0.0997)	(0.1110)	(0.1195)	(0.1414)	(0.0000)	(0.0001)	(0.0002)	(0.0679)	(0.0767)	(0.0939)
α	Coeff.	0.16075	0.15789	0.16041	0.08171	0.08215	0.08284	0.27300	0.27511	0.27648	0.13982	0.14071	0.14169
	Prob.	(0.0000)	(0.0000)	(0.0000)	(0.0003)	(0.0006)	(0.0013)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β	Coeff.	0.83667	0.83895	0.83676	0.85834	0.85724	0.85632	0.98189	0.98070	0.98064	0.87858	0.87705	0.87635
	Prob.	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	Coeff.	-	-	-	0.12882	0.12971	0.13096	-0.07115	-0.07207	-0.07279	0.26293	0.26353	0.26461
	Prob.				(0.0001)	(0.0003)	(0.0006)	(0.0002)	(0.0007)	(0.0011)	(0.0010)	(0.0020)	(0.0033)
AIC		-6.84430	-6.84419	-6.84800	-6.86206	-6.86044	-6.86328	-6.86138	-6.86051	-6.86351	-6.85773	-6.85715	-6.86031
SC		-6.81638	-6.81069	-6.81450	-6.82856	-6.82136	-6.82420	-6.82788	-6.82143	-6.82443	-6.82424	-6.81807	-6.82123
Log likelihood		2913.828	2914.783	2916.402	2922.377	2922.689	2923.894	2922.088	2922.719	2923.993	2920.539	2921.291	2922.633
ARCH-LM		2.50464	2.22589	2.35899	1.79189	1.82863	1.88110	1.28322	1.32843	1.35521	0.93272	0.95850	0.99694
		(0. 1135)	(0.1357)	(0.1246)	(0.1807)	(0.1763)	(0.1702)	(0.2573)	(0.2491)	(0.2444)	(0.3342)	(0.3276)	(0.3181)

Table 4: Estimates of CSCX using different models

		CSCX											
		GARCH			TGARCH			EGARCH			PARCH		
Parameter		Normal	Student's-t	GED	Normal	Student's-t	GED	Normal	Student's-t	GED	Normal	Student's-t	GED
C	Coeff. Prob.	0.00018 (0.3863)	0.00011 (0.5980)	0.00010 (0.6430)	-4.9E-05 (0.8189)	-7.5E-05 (0.7321)	-8.5E-05 (0.6956)	-0.00011 (0.5899)	-0.00015 (0.4883)	-0.00015 (0.4734)	-0.00012 (0.5673)	-0.00016 (0.4610)	-0.00016 (0.4530)
AR(1)	Coeff. Prob.	0.15744 (0.0000)	0.16272 (0.0000)	0.16188 (0.0000)	0.17117 (0.0000)	0.17271 (0.0000)	0.17202 (0.0000)	0.16692 (0.0000)	0.16938 (0.0000)	0.16928 (0.0000)	0.16499 (0.0000)	0.16784 (0.0000)	0.16761 (0.0000)
C	Coeff. Prob.	7.11E-07 (0.1077)	7.01E-07 (0.1313)	7.09E-07 (0.1545)	4.26E-07 (0.2084)	4.28E-07 (0.2249)	4.28E-07 (0.2517)	-0.33123 (0.0001)	-0.33227 (0.0002)	-0.33427 (0.0004)	8.65E-05 (0.1006)	8.69E-05 (0.1221)	8.77E-05 (0.1412)
α	Coeff. Prob.	0.14964 (0.0000)	0.14611 (0.0000)	0.14819 (0.0000)	0.07294 (0.0004)	0.07164 (0.0009)	0.07234 (0.0016)	0.25100 (0.0000)	0.24962 (0.0000)	0.25089 (0.0000)	0.12819 (0.0000)	0.12709 (0.0000)	0.12797 (0.0000)
β	Coeff. Prob.	0.85039 (0.0000)	0.85356 (0.0000)	0.85177 (0.0000)	0.87255 (0.0000)	0.87347 (0.0000)	0.87277 (0.0000)	0.98632 (0.0000)	0.98606 (0.0000)	0.98595 (0.0000)	0.89011 (0.0000)	0.89109 (0.0000)	0.89034 (0.0000)
γ	Coeff. Prob.	-	-	-	0.12114 (0.0002)	0.12222 (0.0004)	0.12294 (0.0007)	-0.06575 (0.0004)	-0.06679 (0.0012)	-0.06728 (0.0017)	0.26217 (0.0018)	0.26752 (0.0037)	0.26849 (0.0051)
AIC		-6.88002	-6.87960	-6.88281	-6.89652	-6.89514	-6.89754	-6.89193	-6.89154	-6.89430	-6.88870	-6.88876	-6.89158
SC		-6.85211	-6.84610	-6.84932	-6.86302	-6.85607	-6.85846	-6.85844	-6.85246	-6.85522	-6.85521	-6.84968	-6.87662
Log likelihood		2929.010	2929.830	2931.197	2937.023	2937.439	2938.457	2935.074	2935.905	2937.080	2933.701	2934.723	2935.925
ARCH-LM		1.25900 (0.2618)	1.03947 (0.3079)	1.14366 (0.2849)	0.64649 (0.4214)	0.59803 (0.4393)	0.63228 (0.4265)	0.35521 (0.5512)	0.32410 (0.5692)	0.34792 (0.5553)	0.19664 (0.6574)	0.16423 (0.6853)	0.18714 (0.6653)

The GARCH, EGARCH and PARCH models exhibit $\alpha + \beta$ is approximately one or more than one in both stock exchange which indicate the volatility is highly persistence and explosive. The effect of shocks will never dry out. On the contrary, under TGARCH the sum of $\alpha + \beta$ is less than one under three distributions. It indicates that shocks to the conditional variance is persistence but not explosive. Since, the sum is less than one that is why there is a tendency of variance to go back to long run mean of the volatility series. So, the shock will dry out very slowly and it is also an indication of long memory of our stock markets.
To select the best model among the models, we use log-likelihood statistics and AIC value. It is found that the log-likelihood statistics of TGARCH model is very large. This result implies that the TGARCH have an attractive representation of daily return behaviors which efficiently captures the temporal dependence of return volatility. On the other hand, AIC value of TGARCH is lower than the others. So, TGARCH model is the best to explain conditional variance of Bangladeshi stock markets.

Table 5: Forecasting evaluation of best fitted models

	DSEX				**CSCX**			
Model	**RMSE**	**MAE**	**MAPE**	**Theil Inequality Coefficient**	**RMSE**	**MAE**	**MAPE**	**Theil Inequality Coefficient**
TGARCH(GED)	0.009198	0.006590	133.8825	0.870773	0.009071	0.006504	189.8353	0.849119
EGARCH(GED)	0.009194	0.006590	132.5748	0.877026	0.009071	0.006502	187.9742	0.850691

In this study we use the estimated TGARCH(1,1) with GED to forecast the volatilities for DSEX and CSCX. In Figure 3(upper two) for initial sample forecast it is observed that the return on DSEX index is stable but shows intense volatility however the modified sample forecast (lower two) the return on DSEX is also stable and shows intense volatility over the period. In Figure 4(upper two) for initial sample forecast it is observed that the return on CSCX index is stable but shows intense volatility however the modified sample forecast (lower two) the return on CSCX is also stable and shows volatility slows towards year end. So in Figure 3 and 4, we can see that the model did a good job. Also we can see that these two markets are highly correlated ($r = 0.9754$) and there is a significant synchronization in their movements. This is not surprising because Dhaka stock exchange and Chittagong stock exchange are the only two stock exchanges in Bangladesh and they are highly interfered by the government.

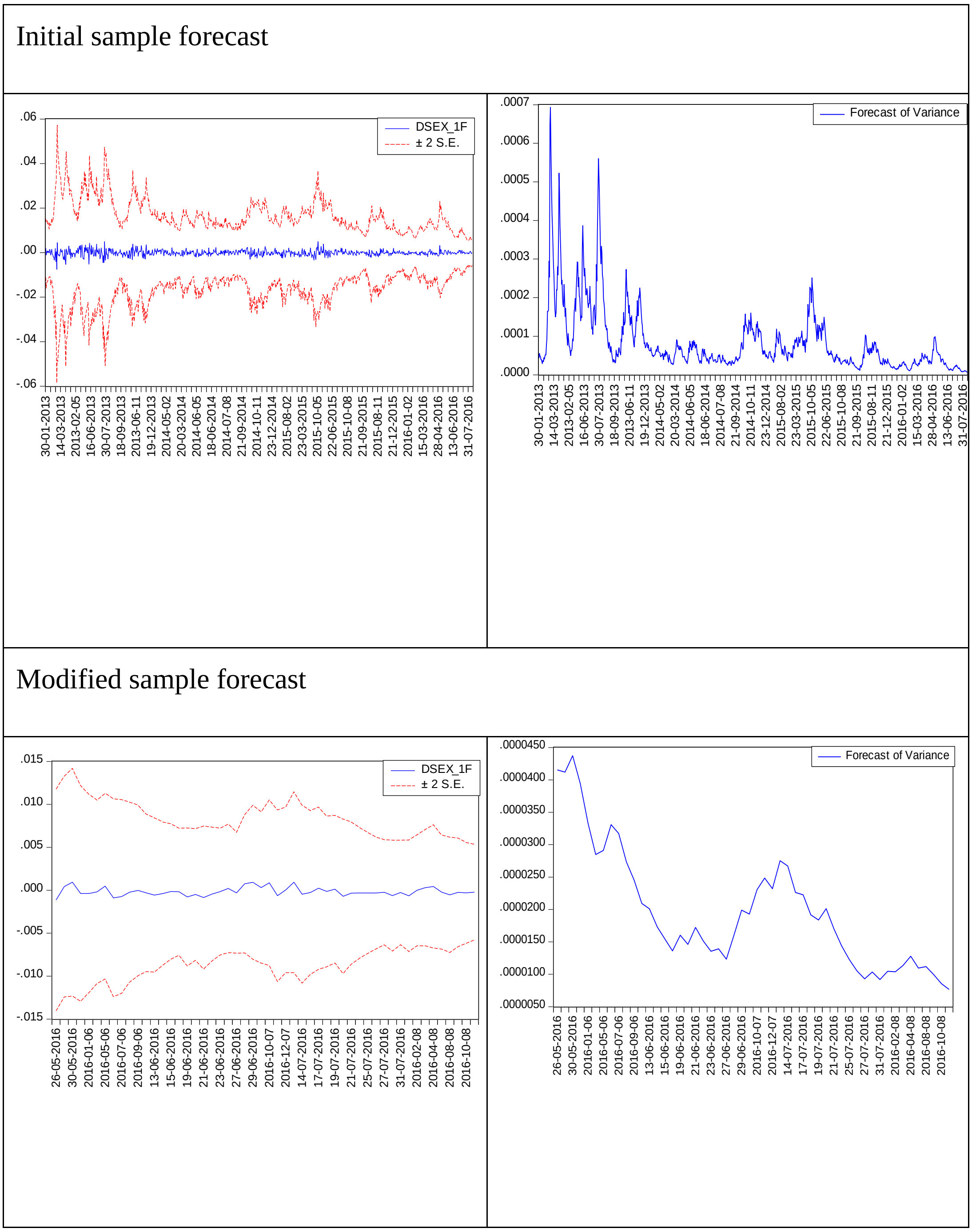

Figure 3: Forecasting of returns in DSEX

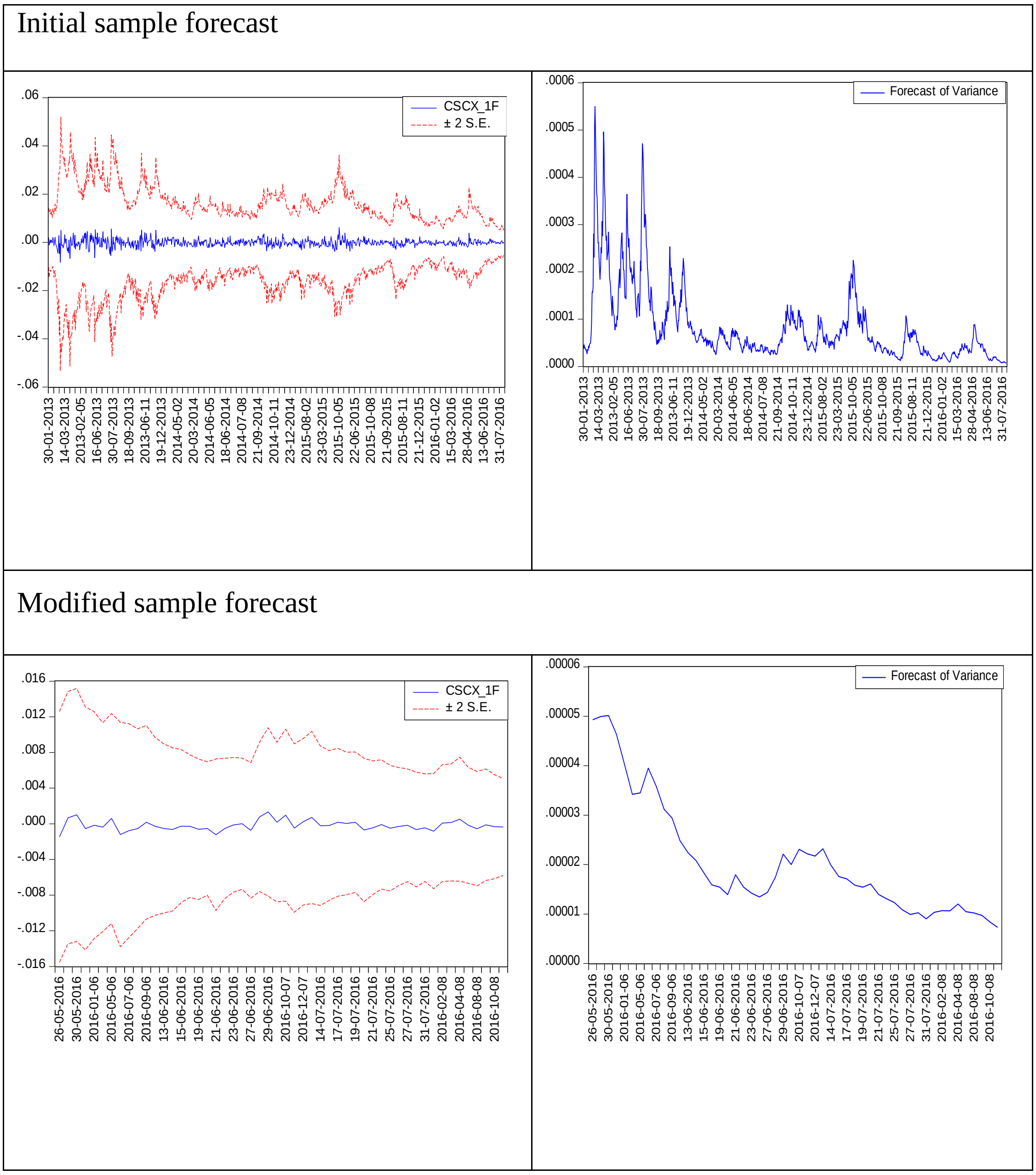

Figure 4: Forecasting of returns in CSCX

4. Conclusion

Using GARCH, EGARCH, TGARCH and PARCH models, the study examines various peculiar aspect of volatility and suggest the best model for forecasting two Bangladeshi stock exchanges. Our empirical analysis provide evidence that the lagged error terms and lagged conditional variance both have significant impact on current volatility in both DSE and CSE. Volatility clustering also prevailed in both markets. It is found that the volatility is highly persistent and old news which is very important in our stock markets. Besides, we have also seen significant leverage effect, that is, bad news creates more impact on volatility than the same magnitude of good news in both markets. Models also reveal that any sock to market takes time to dry out, so it is a strong indication of long memory.

Our results suggest that the TGARCH model reflects an appropriate presentation of return data for both DSE and CSE. This model might be useful for forecasting purpose as it is validated accordingly. This study would be useful for the investors or researchers to determine the future value of share index and there by taking decision for investment.

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