How efficient the GARCH type volatility models are? Evidence from Dhaka Stock Index

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Abstract

Engle and Patton (2000) point out that a volatility model must have the forecasting ability, this is the central requirement. They explore the stylized factors of volatility and observe the ability of GARCH type models to capture those features. In this paper, we aim to evaluate the ability of GARCH type models to capture the stylized factors of Dhaka Stock Exchange (DSE) returns volatility. We consider the sample period from 27th November 2001 to 31st July 2013 for DSE general index and estimate GARCH type models. We made a comparative of different GARCH type models for capturing the stylized factors of the stock index return's volatility.

Keywords: Volatility, GARCH type Models, DSE general Index.

1.Introduction

As Engle and Patton (2000) mention, volatility models must have the ability to forecast future volatility. At the same time, volatility models must have the capacity to capture stylized factors of volatility series. To capture the stylized factors, theoretical researchers are engaged in developing different types of time varying volatility models immediately after the development of Engle(1982)'s ARCH model. To capture different stylized factors exhibited by the volatility series, ARCH type models have been extended in various dimensions including Bollerslev (1986)'s GARCH, to capture the important nonlinearily, asymmetry, and long memory properties in the volatility process (see, e.g., Andersen and Bollerslev, 1998). Other popular extensions of GARCH type models to improve the flexibility of the basic ARCH model are EGARCH (Nelson, 1991) model, GJR-GARCH (Glosten, Jaganathan, and Runkle, 1993), AGARCH (Engle, 1990), APARCH (Ding et al., 1993), TGARCH (Zakoian, 1994) and QGARCH (Sentana, 1995). However, there are few other models including MCMC (see, e.g., Verhofen, 2005 ;Chib, Nardari and Shephard, 2002), support vector machine (see, e.g., Khan, 2011) are also available in literature to capture such stylized factors. We confined our study on GARCH type models only.

The rest of the paper is arranged as follows. A brief review of literatures will be in section 2. Section 3 contains the data description along with summary statistics. Section 4 describes computing models. Section 5 discusses the empirical results and section 6 conclusion.

2. Literature Review

Dhaka stock market is not yet a well established yet. Still the numbers of quality researches on DSE index is limited in the literature. Very limited numbers of scholars tried to modeling and forecasting DSE index return series but there observed plenty research gaps in their works. Basher et al. (2007), which is one of the best ever works on Bangladesh Stock Market, investigate the issue of market efficiency and time-varying risk-return relationship by using ARMA(p,q), GARCH(1,1)-M models. They consider

Gaussian error distribution while the returns series is non Gaussian according to their findings. Chowdhury (1994) observes stock return behavior by using EGARCH-M model considering GED distribution. Chowdhury et al. (2006) investigate how predicted macroeconomic volatility is related to the predicted stock market volatility in Bangladesh by considering only the GARCH (1,1) model to their study. Molla (2009) uses GARCH (1,1), GARCH (2,1) and GARCH (2,2) models to investigate the time varying risk return relationship and persistence of shocks to volatility in Bangladesh stock market and observe that positive skewness and excess kurtosis reveal the non normality of the DSE return series though they do not mention the underlying distribution(s) the considered. Other studies include Hossain and Uddin (2011), Rayhan et al. (2011), Islam et al. (2012), Alam et al. (2013), Muktadir-al-Mukit (2013) and Islam et al. (2014) can be mentioned here.

While thinking about the above mention literatures, there observed significant divergence among model selection, underlying innovation distribution selection. Therefore, this study aims to fit the GARCH type models for Dhaka Stock Indices by considering all possible innovation distributions. R program and E-views software will be used for both estimation and forecasting purpose.

3. The GARCH type models

The general form of the ARCH type models are

$$y_t = \mu_t + \epsilon_t \quad (1)$$
$$\epsilon_t = \sigma_t z_t \quad (2)$$
$$\mu_t = c(\eta|\Omega_{t-1}) \quad (3)$$
$$\sigma_t = h(\eta|\Omega_{t-1}) \quad (4)$$

where $c(\eta|\Omega_{t-1})$ and $h(\eta|\Omega_{t-1})$ are functions of Ω_{t-1}, the information set at time $t-1$ and depend on an unknown vector parameters η, z_t is a i.i.d. process, independent of Ω_{t-1} with $E(z_t) = 0$ and $Var(z_t) = 1$. μ_t and σ_t are the conditional mean and conditional variance respectively. The extensions of ARCH type models are:

i. GARCH Model

Bollerslev (1986) proposed the GARCH model. We use GARCH (1,1) models as

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \;\; \omega > 0, \quad \alpha, \beta \geq 0 \quad (5)$$

where ω, β and α are the parameters, which are assumed to be non-negative to guarantee that volatility is always positive. This model is able to capture the volatility clustering. $|\beta + \alpha| < 1$, implies that the volatility is stationary and the speed for which the shock to volatility decays becomes slower as $\beta + \alpha$ approaches to one.

ii. GJR-GARCH Model

Glosten, Jagannathan and Runkle (1993) proposed the GJR-GARCH model to capture the asymmetry. In this study, we use the GJR-GARCH (1,1) model as

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \lambda\epsilon_{t-1}^2 I_{t-1} \quad (6)$$

where $I_{t-1}$is an indicator function with $I_{t-1} = 0$ if $\epsilon_{t-1} \geq 0$ and with $I_{t-1} = 1$ if $\epsilon_{t-1} < 0$. ω, β, α and λ are the parameters, which are assumed to be non-negative to guarantee that volatility is always positive.

iii. EGARCH Model

It has already been established that the general GARCH model cannot capture the well-known volatility asymmetry phenomenon in stock markets. To capture this phenomenon, we use the Nelson (1991)'s EGARCH model. Specifically, we use the EGARCH (1,0) model as

$$ln(\sigma_t^2) = \omega + \phi[ln(\sigma_{t-1}^2) - \omega] + \theta z_{t-1} + \gamma(|z_{t-1}| - E|z_{t-1}|), \quad |\phi| < 1 \qquad (7)$$

where $E|z_{t-1}| = \sqrt{2/\pi}$, since $z_{t-1}$is assumed to follow standard normal distribution. As EGARCH model specifies the logarithm of volatility, thus, it does not require any non-negativity constraints for the parameters. $\theta < 0$, implies the consistency with the volatility asymmetry in stock markets. In this model, $|\phi| < 1$, implies that the volatility is stationary and the speed for which the shock to volatility decays becomes slower as ϕ approaches to one.

iv. APARCH Model

The APARCH model is proposed by Ding et al. (1993) as an extension of Bollerslev (1986)'s GARCH that nests at least seven GARCH specifications. In this paper, we use APARCH(1,1) model as

$$\sigma_t = \left[\omega + \alpha_1(|\epsilon_{t-1}| - \alpha_n\epsilon_{t-1})^\delta + \beta_1\sigma_{t-1}^\delta\right]^{\frac{1}{\delta}} \qquad (8)$$

where $\omega, \alpha_1, \alpha_n, \beta_1$ and δ are the parameters to be estimated. $\delta > 0$, plays the role a Box-Cox transformation of σ_t. α_n, $(-1 < \alpha_n < 1)$, refers the so-called leverage effect.

All these GARCH type models (symmetric and asymmetric) are estimated using Maximum Likelihood estimators assuming Gaussian distribution, Student *t* Distribution and Generalized Error Distribution (GED). The choice of Student *t* and GED distribution is due to the presence of excess kurtosis in the DSE daily return series. The analysis is done using "E-views" version 7.1 Software and "**R**" version 3.2.1.

4. Data and details

The time series data used for modeling volatility in this paper is the daily closing price of Dhaka Stock Exchange (DSE) General Index over the period from 27th November 2001 to 31st July 2013 resulting in total observation of 2926 excluding public holidays. In this study, daily return (r_t) were calculated as the continuously compounded returns which are the first difference in logarithm of closing prices of DSE general Index of successive days:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) * 100 \qquad (9)$$

Where p_t and $p_{t-1}$are the closing general index of DSE at the current day and previous day, respectively, and Log is Natural Logarithm.

Table 1 Descriptive Statistics of DSE General Index Return series

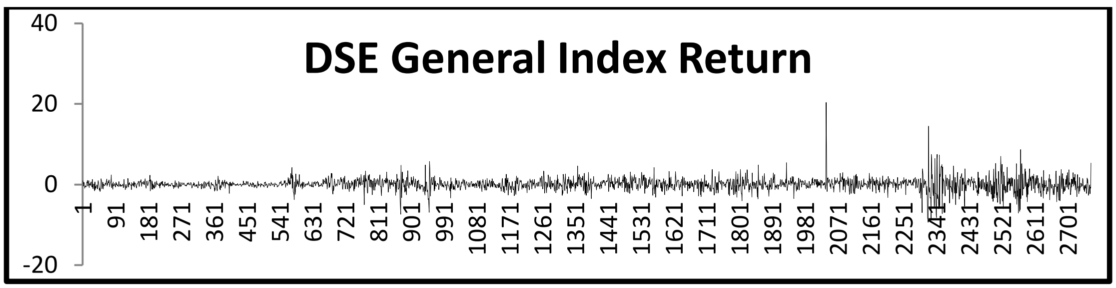
Mean	0.059606	Std. Dev	1.510172
Median	0.050964	Skewness	**0.889866**
Maximum	20.38212	Kurtosis	**22.41277**
Minimum	-9.329968	Jarque-Bera	43781.81

Key: The sample of the period 01/01/2001 to 04/07/2012, there are total 2926 Daily observations. The 5% critical values for Jarque-Bera (i.e., $\chi^2(k)$) is 5.991 (k=2)..

Table 1 shows descriptive statistics of daily index returns and Figure 1 shows the DSE return series respectively. The computed statistics include daily mean return as well as minimum and maximum returns, standard deviation, skewness, kurtosis, and Jarque-Bera.

From the above Table, we observed that the average daily return is 0.059606 with standard deviation 1.510172 that reflecting a high level of dispersion from the average return in the market. The wide gap between the maximum (20.38212) and minimum (-9.329968) return gives support to the high variability of price changes in the DSE. The unconditional distribution of the daily return series is positively skewed (the value of skewness is 0.889866) which means that the right tail is particularly extreme, an indication that the seried has non-symmetric return. High positive kurtosis (the value of kurtosis is 22.41277) indicates long right tail with large positive movements in stock price and not usually matched by equally large negative movements. The large value of kurtosis suggests big shocks of either sign are more likely to be present and the return series is clearly leptokurtic.

Figure 1. The Trend Graph of Daily Returns of DSGN (27th November 2001 to 31st July 2013) and DSE 20 (first January 2001 to 4th July 2012) Index



5. Results

The maximum likelihood estimates for the ARCH and GARCH model for the DSE return series are presented in Table 2. The coefficients of the ARCH parameters (ω and α_1) and GARCH parameters (ω, α_1 and β_1) in the conditional variance equation are highly significant at 1% confidence levels, as measured by their t statistics and all satisfy the non-negativity restrictions of the model for all distributions. The significance of ARCH parameter (α_1) indicates that the news about volatility from the previous day has explanatory power on current volatility. In the same way, statistical significance of GARCH parameter (β_1) does not only indicate explanatory power on current volatility but also suggests volatility clustering in the daily returns of the DSE. The lagged conditional variance estimate has coefficient 0.669154, 0.799798 and 0.783087 for Normal, Student t and GED distribution respectively implying that 0.669154%, 0.799798% and 0.783087% of a variance shock remains the next day. The model with Student t distribution shows higher shock than the other two distributions. Volatility persistence is measured by the sum of α_1 and β_1. From the estimates in Table 2, the DSE daily returns have high persistence in volatility with $\alpha_1 + \beta_1 = 1.019652, 1.025108$ and 1.038385 for Normal, Student t and Generalized Error distribution respectively. High persistence implies that average variance will remain high since increases in conditional variance due to shocks will decay slowly (Rachev et al., 2007). Evidence of persistence in volatility shocks abound in literature (see, Emenike, 2010; Oskooe and Shamsavari, 2011). According to AIC and BIC, among two symmetric models (ARCH and GARCH), GARCH model is the best fitted model with Student t distribution. The ARCH-LM test statistics did not exhibit additional ARCH effect. This shows that the variance equations are well specified.

The GARCH-M model is estimated by allowing the mean equation of the return series to depend on function of σ^2 the conditional variance. Table 2 presents the estimation results for the mean equations. The estimated coefficient (risk premium) of σ^2 in the mean equation is positive for all three distributions, which indicates that the mean of return sequence considerably depends on past innovation and past conditional variance. In other words, conditional variance used as proxy for risk of return is positively related to the level of return. This result show that as volatility increases, the returns correspondingly increase by a factor of 0.006963, 0.015260, and 0.007871 under Normal, Student *t* and Generalized Error distribution respectively. These results are consistent with the theory of a positive risk premium on stock indices which states that the higher returns are expected for asset with higher level of risk. The ARCH and GARCH coefficients are significant in all periods. The null hypothesis that there is no ARCH effect is accepted.

Table 2 Estimates of the Parametric Volatility Models (Symmetric) for DSE General Index

ARCH		**Distribution**		
Parameter		**Normal**	**Student *t***	**GED**
ω (constant)		1.284026***	0.995079***	0.995923***
α_1 (ARCH effect)		0.413433***	0.763041***	0.617928***
Log Likelihood		-4987.648	-4640.888	-4667.453
AIC		3.415428	3.178849	3.197025
BIC		3.423612	3.189079	3.207255
ARCH LM	$N*R^2$	0.042472	0.178107	0.158376
	Prob.Chi-Square	0.8367	0.6730	0.6907
GARCH				
Parameter				
ω (constant)		0.121439***	0.018863***	0.026604***
α_1 (ARCH effect)		0.350498***	0.225310***	0.255298***
β_1 (GARCH effect)		0.669154***	0.799798***	0.783087***
$\alpha_1 + \beta_1$		1.019652	1.025108	1.038385
Log Likelihood		-4768.754	-4428.376	-4483.946
AIC		3.266339	3.034126	3.072149
BIC		3.276568	3.046402	3.084425
ARCH LM	$N*R^2$	0.051959	0.019089	0.021624
	Prob.Chi-Square	0.8197	0.8901	0.8831
GARCH in Mean				

λ (risk premium)		0.006963	0.015260	0.007871
μ (constant)		0.134461***	0.041486**	0.048994***
Log Likelihood		-4768.565	-4427.384	-4483.578
AIC		3.266894	3.034132	3.072581
BIC		3.279170	3.048454	3.086903
ARCH LM	$N{*}R^2$	0.050639	0.017446	0.020773
	Prob.Chi-Square	0.8220	0.8949	0.8854

Key : AIC= Akaike Information Criterion and BIC (SC)= Schwarz Criterion

Table 3 presents estimates obtained from EGARCH, PGARCH and GJR-GARCH asymmetric volatility models. These estimates are used to examine the existence of asymmetry in stock returns volatility of the DSE. According to reported EGARCH results, the γ coefficient, which measures asymmetric effect, is less than zero for all Normal, Student *t* and GED distribution. The negative γ coefficients are shown by the marginal significant level. Marginal significance levels less that the critical level lead to rejection of the null hypothesis of zero coefficients. The marginal significance level for the γ coefficient of the EGARCH model is clearly significant at 1% confidence level. Statistically significant γ coefficient indicates that the null hypothesis of no asymmetric effects in the volatility of DSE is false. In other words, there is an asymmetric effect in the volatility of stocks returns of the Dhaka Stock Market. In contrast to leverage effect, the γ coefficient is negative, suggesting that negative shocks tend to produce higher volatility in the immediate future than positive shocks of the same magnitude in the Dhaka Stock Market. The ARCH-LM test statistics did not exhibit additional ARCH effect. This shows that the variance equations are well specified.

Furthermore, the GJR-GARCH model estimates in Table 3 also confirm the evidence of asymmetry in the stock returns volatility of the DSE. Positive (negative) γ coefficient indicates that negative (positive) shocks tend to produce higher volatility in the immediate future than positive (negative) shocks. According to results given in Table 3 the γ coefficient for GJR-GARCH model is positive, indicating that negative shock tends to produce higher volatility in the immediate future than positive shocks of the same magnitude, thereby suggesting absence of leverage effect in DSE. Evidence of volatility clustering given in GARCH estimates above is also confirmed by high statistical significance of the GARCH term (β_1) and ARCH term (α_1). Similarly, sample evidence shows that volatility clustering is persistent in DSE stock returns on the basis of sum of $\alpha_1 + \beta_1 + \gamma/2$=1.0243935, 1.0262805 and 1.0388905 with Normal, Student *t* and Generalized error distribution respectively. This implies that volatility shocks can be predicted for several days in the DSE. The rejection of leverage effects in consistent with some of the prior studies (see, e.g., Ogum et al., 2005; Saleem, 2007; Gc, 2008); but disagree with others (see, e.g., Nelson, 1991; Okpara, 2011).

Unlike other GARCH models, in this model, the standard deviation is rather modelled as against modelling of variance in most of the GARCH-family of models. Results of PGARCH are presented in Table 3. From the results of PGARCH, the estimated coefficient γ is significant and positive with Normal, Student *t* and Generalized Error distribution, indicating that positive shocks are associated with higher volatility than negative shocks. The ARCH-LM test statistics did not exhibit additional ARCH effect. This shows that the variance equations are well specified.

Table 3 Estimates of the Parametric Volatility Models (Asymmetric) for DSE General Index

EGARCH		**Distribution**		
Parameter		**Normal**	**Student *t***	**GED**
ω (constant)		-0.297595***	-0.245530***	-0.253380***
α_1(ARCH effect)		0.490134***	0.340723***	0.367002***
γ (Leverage effect)		-0.151436***	-0.070430***	-0.080679***
β_1(GARCH effect)		0.894206***	0.962577***	0.953130***
Log Likelihood		-4722.140	-4426.781	-4476.819
AIC		3.235128	3.033719	3.067957
BIC		3.247404	3.048041	3.082279
ARCH-LM	$N*R^2$	0.043014	0.014670	0.017122
	Prob.Chi-Square	0.8357	0.9036	0.8959
PGARCH				
ω (constant)		0.125028***	0.026076***	0.036067***
α_1(ARCH effect)		0.284535***	0.209747***	0.224738***
γ (Leverage effect)		0.294937***	0.114777***	0.135680***
β_1(GARCH effect)		0.710133***	0.824403***	0.811023***
δ (Power Parameter)		1.290461***	1.187872***	1.159207***
Log Likelihood		-4726.864	-4414.578	-4469.404
AIC		3.239045	3.026054	3.063568
BIC		3.253367	3.042422	3.079935
ARCH-LM	$N*R^2$	0.028643	0.012007	0.012388
	Prob.Chi-Square	0.8656	0.9127	0.9114
GJR-GARCH				
ω (constant)		0.116147***	0.020172***	0.029738***
α_1(ARCH effect)		0.194000***	0.183346***	0.198469***

γ (Leverage effect)		0.312229***	0.090321***	0.125391***
β_1(GARCH effect)		0.674279***	0.797774***	0.777726***
$\alpha_1+\beta_1+\gamma/2$		1.0243935	1.0262805	1.0388905
Log Likelihood		-4733.768	-4423.432	-4477.412
AIC		3.243084	3.031428	3.068362
BIC		3.255360	3.045749	3.082684
ARCH-LM	$N*R^2$	0.065717	0.022546	0.027452
	Prob.Chi-Square	0.7977	0.8806	0.8684

Key : AIC= Akaike Information Criterion and BIC (SC)= Schwarz Criterion

6. Conclusion

Table 1 shows the descriptive statistics for DSE general index. We observe that all these results go with the stylized facts those have already been ascertained, i.e., the unconditional distribution of the return series is not normal, the series is highly skewed and kurtosed.

The AIC, BIC and LL values symmetric models (ARCH, GARCH, GARCH-M) and asymmetric models (EGARCH, PGARCH AND GJR-GARCH) are shown in Table 2 while Table 3 shows different estimated values of parameters for DSE general index for the PGARCH model. We observed that the estimated coefficient γ is significant and positive with Normal, Student *t* and Generalized Error distribution, indicating that positive shocks are associated with higher volatility than negative shocks. The minimum values of AIC, BIC and LL are advocating PGARCH for the best fitted model for DSE general index.

It is also observed that in symmetric models, ARCH (α) and GARCH (β) parameter are significant and positive in all the estimations. The sum of the ARCH and GARCH parameter ($\alpha + \beta$) is greater than one which indicates high volatility persistence present in the index. In asymmetric models, all models show asymmetric parameter is statistically significant for DSE general index where PGARCH and GJR-GARCH model shows positive values and EGARCH shows negative values. Therefore, we may conclude that not all the GARCH type models can incorporate all the stylized factors of the return series.

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