TIME-VARYING VOLATILITY DYNAMICS OF DHAKA STOCK EXCHANGE (DSE) USING GARCH-TYPE MODELS

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ABSTRACT

Our study in this paper examines the changes in volatility dynamics of Bangladesh stock market, due to stock market crash back in 2010 using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. Both symmetric and asymmetric GARCH models were used to estimate the conditional volatility in daily returns of the main stock exchange of Bangladesh namely as the Dhaka Stock Exchange (DSE). Using the closing values of DSE General (DGEN) and DSE broad (DSEX) indices, we conduct our analysis by keeping the crash period of 2010 in focus and dividing the data series into three sub-periods namely as crash, pre-crash and post-crash periods. The data series exhibit evidences of skewness, kurtosis and deviations from normality as expected from Finance literature. The unit root test concludes that the data series is not stationary at level but become stationary when we take returns of the series into consideration. The conditional variance is found to be highly persistent with leverage and asymmetric effects. Our results also indicate that asymmetric GARCH models are better fitted to model volatility dynamics than the symmetric GARCH model for all sub-periods. Lastly, the comparison among various model parameters in different sub-periods in our study also exhibit significant change in volatility patterns of DSE from pre-crash to post-crash period as indicated by ARCH, GARCH, Leverage and Power coefficients.

Key words: Volatility, Symmetric GARCH, Asymmetric GARCH, DSE, Leverage, Stock market crash

INTRODUCTION

Volatility of the financial market is considered as one of the major indicators of the dynamic fluctuation in stock prices around the world (Raja & Selvam, 2011). Stock market volatility is synonymous with risk and unlike the constant volatility assumption of Classical Linear Regression Model (CLRM); the stock market volatility is not stable over time as it changes frequently. This time-varying nature of volatility and the asymmetry within a financial time series have become an important financial research area in recent times.

Historically most of the stock market crashes had significant influence on volatility patterns of the affected markets. Bangladesh stock market also experienced severe market crash back in 1996 and then again most recently in 2010. Same as global markets, volatility patterns of

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Bangladesh stock market was also expected to change after these market crashes. While many literatures related to market crash in 1996 tried to uncover reasons and aftermath of that financial crisis, a little study has been made till date regarding the impact of 2010 stock market crisis and its impact on the market return volatility.

Our main objective for this research is to capture the time-varying volatility dynamics of DSE through using various univariate symmetric and asymmetric GARCH model parameters and their coefficients. We use time series data of the DSE indices to find the best fitted GARCH model/models. This helps us to analyse the conditional volatility of the market. Besides, we also focus on the change of coefficient values for selected model parameters due to change in volatility dynamics before and after the 2010 stock market crash.

Various studies so far have been made regarding the impact of 2010 stock market crisis in Bangladesh. However to the best extent of our knowledge, none of these studies have focused on the shifting patterns of time-varying conditional volatility due to the market crash using asymmetric GARCH parameters. Thus, our study will help to understand the market dynamics more thoroughly and enrich literatures related to volatility movement pattern due to market crash for the Bangladeshi stock market.

LITERATURE REVIEW

In the case of financial time series, constant volatility assumption over a period of time is statistically insignificant and logically inconsistent (Campbell, Lo, & MacKinlay, 1996). In most cases, the volatility of a financial time series actually moves in 'cluster' which means large(small) change in asset price will follow a further large(small) change (Mandelbrot, 1963). Therefore, unlike the Homoscedasticity assumption of Classical Linear Regression Model (CLRM), error variance of a financial time series is not constant. To capture the impact of lagged residuals on the volatility exhibited by financial time series, Autoregressive Conditional Heteroscedasticity (ARCH) class of models were proposed (Engle R., 1982).

Since then, different studies of investment and financial market volatility have been made by Hsieh (1984), Akgiray (1989), Engle (1990), Engle and Mustafa (1992) and others using the ARCH models to confirm and capture the existence of ARCH effect in various global financial markets. With the use of high frequency daily and weekly data, significant ARCH effects are shown in different global stock markets (Diebold F. X., 1988), (Drost & Nijman, 1993). This ARCH effect exists mainly due to the amount/quality of information that reaches in financial markets and the time required between information arrivals and processing by market participants. However, with the decrease in data frequency, the ARCH effect actually fades away (Diebold & Nerlove, 1989).

Various studies are made to conduct the presence of ARCH effect in different financial markets. For instance, Brailsford and Faff (1996) use ARCH and simple regression models to capture and forecast the volatility pattern for Australian stock market. However, a major constraint of these ARCH type models is their sensitivity to the error statistics which are mainly used to measure the model forecasting accuracy. To overcome this constraint, a new improved extension of the ARCH, namely as GARCH model, was proposed (Bollerslev, 1986). GARCH performs better than ARCH and simple regression models in capturing volatility dynamics using Fourier analysis. The model eases the process of calculating diffusion process of volatility for a particular time point (Barucci & Reno, 2002b). Besides, GARCH has superior forecasting power over other linear and ARCH type models (Akgiray, 1989). Akgiray (1989) forecasts the monthly variance using 4 linear and non-linear models namely as Historical Estimate, Exponentially Weighted Moving Average (EWMA), ARCH and GARCH models and among these, GARCH model outperforms others and the forecasts obtained from this model are highly accurate and less biased.

GARCH type models are able to capture and forecast the time-varying conditional variance of a financial time series which has past random changes in its return. Observation reveals that the simple first order symmetric GARCH (1, 1) model performs better to capture the conditional volatility dynamics of time series compared to historical standard deviation and EWMA models. However, this GARCH (1, 1) model lacks forecasting accuracy because of its simplistic symmetric nature in contrast to the asymmetric behaviour of the financial market volatility (Erdington & Guan, 2004). To capture this asymmetry of the market (popularly known as leverage effect), several improvements of the original GARCH model such as the Exponential GARCH (EGARCH), the Power GARCH (PGARCH), the Threshold GARCH (TGARCH) and others are proposed. Several studies conducted by Pagan and Schwert (1990), Lee (1991) and Randolph & Najand (1991) suggest that the simple GARCH is only accurate in period with small volatility changes, thus proving that the model is inferior and has persistent forecast capability compared to other asymmetric GARCH models. In addition, Taylor *et al.* (2010) suggests that although model free volatility expectation and at-the-money (ATM) implied volatility out- perform other volatility models, asymmetric GARCH models are still better for short forecasting horizon period.

In recent years, volatility modelling in emerging stock markets has gained much popularity mainly due to the global shift of investors' focus from developed markets to the developing emerging markets. Studies such as Moosa and Al-Loughani (1995) and Saatcioglu and Starks (1998) examine the volatility dynamics of different emerging stock markets. Bekaert and Harvey (1995) concludes that the dynamics of volatility is difficult to capture in emerging markets unlike developed markets although the paper confirms the importance of world factors to model the emerging market volatility. Later, a further study by Bekaert *et al.* (1998) and A. Ng (2000) exhibit the applicability of univariate asymmetric GARCH process in emerging markets and thus introduce significant improvement in the volatility modelling of emerging market. Other studies such as Poshakwale and Murinde (2001) observes persistent volatility using the GARCH in Mean (GARCH-M) technique on Hungary and Poland stock markets while Siourounis (2002), Bologna and Cavallo (2002) and Gonzalez *et al.*

(2003) find out the best suited GARCH models for Athens, Italian and Mexican stock markets respectively by using different GARCH-type models.

Recently Asian emerging stock markets have gained significant attention and discussions due to economic growth of China, India and several other East Asian countries. Researchers such as Raju and Ghosh (2004) observes a high volatility pattern for Indian and Chinese stock markets compared to other emerging markets.

Studies of Rijo (2004), Kaur (2004), Padhi (2006), Radha & Thenmozhi (2006) and Fahimifard *et al.* (2009) have found the presence of ARCH effect in various Asian stock markets. Their studies conclude that non-linear ARCH/GARCH-type models actually can perform better than different linear models for these markets. However, other studies such as the one of Mukherjee *et al.* (2011) reveals the presence of asymmetric leverage effect for Asian, mainly Indian stock market. The paper suggests that the asymmetric EGARCH can capture the market dynamics of Indian SENSEX index better compared to TARCH model as the index return data exhibits considerable amount of asymmetry with higher skewness. Hassan & Shamiri (2007) also confirms the better applicability of EGARCH model to explain the asymmetry of Singapore and other important Asian stock markets.

Literatures related to emerging and developed markets volatility dynamics is rich. However, a little has been done so far with Bangladesh and other frontier markets, mainly due to lack of data and size dimension in these markets. Researches such as Haque *et al.* (1998) examines the risk return pattern and market efficiency of DSE and the effect of automated trading system on this pattern. In addition, Hassan and Maroney (2004) analyses the effect of thin trading and non-linearity on DSE market efficiency by fitting a cubic function of stock and AR(1) return processes using data over 13 years period. The study of Chowdhury and Ratan (2012) estimates and forecasts volatility of All Share Index (DSI) using symmetric GARCH and asymmetric GJR-GARCH models for the market return data of 2005-2010 period. The study concludes that the GJR-GARCH model can capture the market dynamics better compared to simple GARCH model. Other studies such as Huq *et al.* (2013) examines modelling and forecasting ability of ARCH, GARCH, TGARCH and EGARCH on DSE data for a period of 2010-2013. The results of this study shows that GARCH (1, 1) and GARCH (2, 1) models provide superior performance to capture conditional volatility dynamics for this period compared to other models.

The stock market of Bangladesh has experienced two major crashes back in 1996 and 2010. As shown by developed and emerging markets, the volatility patterns of stock indices actually shift after each market crash. Therefore, it's essential to analyse the volatility dynamics during the market crash period to get a full understanding about volatility pattern change. However, little has been made so far regarding the relationship between stock market crash and volatility change for Bangladesh. For example, Imam & Amin (2004) divides 1996 market crash period into two sub-periods: pre and post-crash and applies symmetric GARCH model for both these sub-periods. The result of this test exhibit different GARCH parameter values for these sub-periods. Imam & Amin (2004) explains that the presence of high volatility pattern in 1996 post-crash period and the change in the behaviour of investor after market crash was responsible for these parameter values.

Same as 1996, the market crash in 2010 has also changed market dynamics, policy regulations and trading patterns of DSE. Studies in Choudhury (2010), Saha (2012), and Sarker & Nargis (2012) try to expose reasons behind this severe market crash and the implication of this crash on different stakeholders. However, no study related to volatility patterns before and after 2010 market crash period has been conducted till date to the best extent of our knowledge. In addition, unlike Imam & Amin (2004), it is also essential to test asymmetric GARCH models for Bangladeshi stock market as these models have superior predictability than the symmetric ones and they can improve the literature by enabling us to understand reasons behind the true shift of market volatility dynamics from before crash to after crash period in 2010.

DHAKA STOCK EXCHANGE AT A GLANCE

Dhaka Stock Exchange (DSE), the main bourse operating in Bangladesh, began its trading back in 1956 with a total number of 196 listed securities and USD 0.051 billion paid up capital (Chowdhury A. R., 1994). As of June 2014, the market capital of DSE has reached at USD 38.223 billion (see table 1 below).

Table 1: DSE Market Highlights

Key Indicators of DSE	June 30, 2006	June 30, 2014	% Change
	(numbers)	(numbers)	
Listed Companies	256	263	2.7%
Mutual Funds (MFs’)	13	41	215.4%
Debentures Issuers	8	8	0.0%
Treasury Bonds Issuers	26	221	750.0%
Corporate Bonds Issuers		3	
Total No. of Listed Securities	*303*	*536*	*76.9%*
	(million numbers)	(million numbers)	
Listed Companies	139.050	4304.610	2995.7%
Mutual Funds (MFs’)	16.130	408.040	2429.7%
Debentures Issuers	0.040	0.040	0.0%
Treasury Bonds Issuers	0.020	0.550	2650.0%
Corporate Bonds Issuers		0.630	
Total No. of Listed Securities	*155.230*	*4713.870*	*2936.7%*

Annual Traded Securities (in Billion Numbers)	0.593	24.318	4002.3%
Annual Traded Securities (in USD Billion)	0.598	14.620	2344.8%
	(USD Billion)	(USD Billion)	
Capital Issued for Companies & MFs'	0.840	6.187	636.5%
Issued Treasury Bonds	0.273	7.135	2512.1%
Issued Corporate Bonds	0.000	0.081	
Total Issued Capital	*1.113*	*13.404*	*1104.0%*
	June 30, 2006	**June 30, 2014**	
Total Market Capital (in USD Billion)	2.798	38.223	1266.3%
Market capital as % of GDP	7.6%	24.8%	
Index Point	1339.53(DGEN)	4480.52(DSEX)	234.5%
YoY % Change in Index Point	-21.8%	9.2%	

As a Public Limited Company operating in Bangladesh, DSE is regulated by its Articles of Association along with Bangladesh Securities and Exchange Ordinance, 1969, the Companies Act, 1994 and the Securities and Exchange Commission (SEC) Act, 1993. DSE has provisions for 500 members and this membership is open to home as well as foreign investors. The trading activity of DSE is operated through an automated on-line system every day except public holidays. Four categories of shares are traded in DSE namely as 'A', 'B', 'N' and 'Z'. These categories are made mainly based on companies' variability of earning and their dividend payment ability to investors. All transactions made in a day are settled after netting and cleared through the DSE Clearing House on the 2nd working day for category 'A', 'B' and 'N' shares and on the 10th working day for category 'Z' shares, calculated from the date of trading.

The current major index that is maintained, monitored and used as a reference at DSE is known as DSE Broad Index (DSEX). Designed and developed under 'DSE Bangladesh Index Methodology' by S&P Dow Jones indices, DSEX index was introduced on 27th January, 2013 (with an index value of *4055.90645*) as a reformative measurement by the DSE authority after the stock market crash in 2010. Before DSEX, the main index was the DSE General Index (DGEN) which was discontinued right after introducing the DSEX.

METHODOLOGY

A financial time series is a sequence of data points, measured typically at successive times spaced at uniform time intervals (Rayhan, Sarker, & Sayem, 2011). To model and forecast with time series data, first we need to figure out whether the data in consideration are stationary or not. Stationarity of a time series can be checked by finding out the presence of unit root for that series. The Augmented Dickey Fuller (ADF) test is a renowned method to check the unit root and thus the Stationarity of the data set.

Before applying the ARCH/GARCH models on a time series, we first need to figure out whether the 'ARCH effect' presents in a given data set. There are several procedures to test the 'ARCH effect' within a time series. Among these procedures, ARCH Lagrange Multiplier (LM) test is the most prominent one. ARCH-LM test considers a null hypothesis of the presence of no ARCH. According to (Bollerslev, 1986), the LM statistic follows an asymptotic χ^2 distribution where the degree of freedom under null hypothesis is q. If the evaluated test statistics is greater than $\chi^2_{1-\alpha}(q)$, the null hypothesis of no ARCH effect is rejected at a level of α which means a significant 'ARCH effect' exists in the time series and ARCH/GARCH models can be applied in this series to capture its time-varying volatility dynamics.

The ARCH (Engle R., 1982) model is one of the most extensively used time varying model in Finance to model volatility dynamics. The general form of an ARCH (q) process is shown as

$$\sigma_t^2 = \alpha + \sum_{i=1}^{q} \beta_i \varepsilon_{t-1}^2$$

As the ARCH (q) models volatility, the value of α and β_i should always be greater than zero. Besides, the sum of α and β_i should always be greater than 1 to make the process stationary. However, a problem with ARCH (q) model is that the conditional standard deviation modelled in this process has high frequency oscillation with volatility coming with short bursts. To overcome this problem, Bollerslev (1986) extended the ARCH (q) process by taking the lag value of conditional variance in the modelling process and this new improved and extended process is known as GARCH model. The general specification of a simple GARCH (p, q) model is given below:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2$$

The 2nd part of the model $\alpha_i \varepsilon_{t-1}^2$ is known as ARCH component whereas the last part with lagged conditional variance $\beta_i \sigma_{t-1}^2$ is known as GARCH component. This simple GARCH (p, q) process has problem in capturing market dynamics as this process is a symmetric process. However, most of the financial time series data are characterized by their asymmetric nature in conditional variance which is known as the 'leverage effect' which simple GARCH (p, q) can't model. simple GARCH (p, q) process is restricted from considering the asymmetric effect as the positive and negative shock will have same symmetric response in simple GARCH model (Brooks, 2002) which is unlikely to observe in real market.

To capture this asymmetric shock in conditional variance, the Exponential GARCH (EGARCH) model was proposed by Nelson (1991). EGARCH is modelled using the natural logarithm of the conditional variance and this conditional variance is allowed to vary over time as a function of the lagged error terms rather than lagged squared errors. The general form of an EGARCH (p, q) model is given as below:

$$\ln(\sigma_t^2) = \alpha + \sum_{i=1}^{p} \alpha_i \ln(\sigma_{t-1}^2) + \sum_{j=1}^{q} \beta_i \frac{\varepsilon_{t-j}}{\sigma_{t-j}} + \sum_{k=1}^{r} \gamma_i \frac{\varepsilon_{t-k}}{\sigma_{t-k}}$$

The exponential structure of the EGARCH allows the model conditional variance to be always positive even though the parameters can be negative. Thus, EGARCH model makes it redundant to impose non-negativity restrictions within the model. The presence of the asymmetric market condition can be confirmed by testing whether the parameter γ_i is significantly different from zero. If γ_i is significantly different from zero, then the asymmetric effect exists within the financial time series.

Other asymmetric GARCH models such as the Threshold GARCH (TGARCH) proposed by Zako¨ıan (1994) actually captures the asymmetries within a financial time series using a dummy variable. The specification of the TGARCH model is given as below:

$$\sigma_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i} + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j}\, 1(\varepsilon_{t-j} < 0) + \sum_{k=1}^{z} \beta_k\, \sigma_{t-k}$$

Here, $\varepsilon_{t-1}^2 1(.) = 1$ if $\varepsilon_{t-j} < 0$ and $\varepsilon_{t-1}^2 1(.) = 0$ if $\varepsilon_{t-j} > 0$ .If the coefficient has positive values, it indicates the presence of asymmetries known as 'leverage effect'.

Unlike the other asymmetric models, the Power GARCH (PGARCH) proposed by Ding *et al.* (1993), models standard deviation instead of the variance. An optional parameter γ_i is added within this process to capture the asymmetry up to order r. The PGARCH model also allows estimating the power parameter δ instead of imposing the restriction from outside of the model. The general specification of PGARCH (p, q) is given below:

$$\sigma_t^{\delta} = \alpha_0 + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-1})^{\delta} + \sum_{j=1}^{q} \beta_j\, \sigma_{t-1}^{\delta}$$

Here, α_i and β_j are the ARCH and GARCH parameters, γ_i is the asymmetric 'leverage effect' parameter and δ is the power parameter. When $\delta = 2$, the above equation transforms into a classical GARCH model with a parameter to capture leverage effect. However, when $\delta = 1$, the equation becomes an estimation of the conditional standard deviation.

DATA FOR ANALYSIS

We have used an extensive period of time series data comprising of 15 years starting from 27th January 2000 to 4th August 2015. Daily closing values of DSE indices have been taken for this selected time frame from the DSE library. There were a total of 3402 observations excluding the public holidays. To calculate daily returns, we have taken log differences of the daily closing prices.

The stock market crash of 2010 resulted in collapsing the General Index for an extended period of time. During the market collapse the deviations of the stock prices were significantly different from any other period. To witness the change in the volatility pattern and asymmetry of market returns during this crash, we have divided the whole sample into three distinct sub-periods; Pre-Crash, Crash and Post-Crash. Figure 1 in the Appendix shows that prior to the market crash, the General Index of the Dhaka Stock Exchange namely as DGEN was relatively stable. We have taken this comparatively stable period from 27th January 2000 to 30th December 2009 as the pre-crash period. The crash period starting from 3rd January 2010 to 27th January 2013 covers both the bullish effect experienced in the market for an extended period of time before stock market crash and the bearish force associated with the market crash. Both in the pre-crash and crash period, the closing values of the DGEN index were taken. After the stock market crash the DGEN was replaced by the DSEX. Therefore, we have taken the index value data of the post-crash period i.e. from 28th January 2013 to 4th August 2015 from the DSEX.

Summary Statistics

We have given descriptive statistics of the DGEN and DSEX return series for the three sub-periods in table 2. The mean return is the highest in pre-crash period and naturally the lowest with a negative mean return in crash period. The daily standard deviation is found to be the highest during crash period indicating a high level of fluctuations in the daily returns of the DGEN. In the post-crash period the standard deviation of the daily return series again have fallen down and become almost similar to that of the pre-crash period. Besides these, there are evidences of asymmetric tails as the returns are negatively skewed in the post-crash period and positively skewed in other two periods. We have also found highly leptokurtic return series in the pre-crash period as these are more centred on the mean value. When the data series is leptokurtic, large price movements are more frequent than small ones and the central peak becomes narrower with fat tails. Our Jarque-Bera normality test statistics also reject the normal distribution null hypothesis at 1% level of significance.

Table 2: Summary Statistics

Particulars	Pre-Crash	Crash	Post-Crash
Mean	0.000834	-0.000114	0.000292
Median	0.000509	0.000482	0.000000
Maximum	0.203821	0.144799	0.036847
Minimum	-0.073589	-0.093300	-0.053584
Std. Dev.	0.011730	0.021796	0.010450
Skewness	2.446955	0.100944	-0.140519
Kurtosis	48.646040	7.955294	5.000957
Jarque-Bera	181421.6000	754.2680	101.7301
Sum	1.722449	-0.083688	0.174807
Sum Sq. Dev.	0.284140	0.349176	0.065195
Observations	*2066*	*736*	*598*

ANALYSIS OF THE VOLATILITY

Test for Stationarity

To test the Stationarity of data set, we have used Augmented Dickey Fuller (ADF) unit root test as prescribed by Dickey and Fuller (1981) for different time periods. According to the test results given in table 6 of the appendix, data series in each sub-period is not stationary at level. However, we have found the significant ADF test statistics of the return series at 1% level in each of these sub periods. We conclude that the data series is not stationary at level but stationary when log difference is taken.

TEST FOR HETEROSCEDASTICITY

Before applying any of the ARCH/GARCH methods to model volatility, it is recommended to test for the presence of ARCH effect in the residuals of return series. Thus, we have conducted ARCH-LM test on the residuals of the return series for the lag lengths of 1, 5 and 10. Table 7 in the appendix summarizes the results of the ARCH -LM test. The p values of ARCH-LM test during crash and post-crash periods reject null hypothesis of no ARCH effect at 1% significance level for all lag lengths. On the other hand during pre-crash period, there are evidences of ARCH effect at 10% significance level for lag 1 only. Therefore, the presence of ARCH effect in the residuals of data series is more evident in the crash and post-crash period compared to the pre-crash one.

MODELLING VOLATILITY

As the results of ARCH-LM test in table 6 shows momentous presence of ARCH effect in the residuals, we can now apply selected GARCH- models for these three separate sub-periods. According to Brooks (2002), GARCH models of smaller lags are sufficient to detect the volatility clustering effect. Therefore, all GARCH models are taken with (1, 1) lags. Moreover, we have used both symmetric and asymmetric GARCH models to analyse the daily stock return volatility dynamics for these three sub-periods.

PRE-CRASH PERIOD

In the pre-crash period, we have found significant ARCH and GARCH effects at 1% level in all selected GARCH models. Moreover, as observed in GARCH models of other stock markets, the sum of ARCH and GARCH coefficients are found closed to 1 in all cases, thus concluding the presence of highly persistent shocks in the conditional variance. A large total sum of these coefficients implies that a large positive or a negative return will lead future forecasts of the variance to be high for a prolonged period. The asymmetric GARCH models used here also successfully capture leverage effects experienced in the DGEN returns as we have rejected the null hypothesis of no leverage effect was 1% significant level. The coefficient of the power parameter is also significantly different from both 1and 2 at 1% significance level.

Table 3: GARCH models in the Pre-Crash period

Particulars	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)	PGARCH (1,1)
Risk Premium	0.089263 (.2064)	-0.070127 (.3178)	0.170489 (.0181)	-0.067166 (.3451)
α_0 (Constant)	1.15E-05 (.0000)	1.11E-05 (.0000)	-1.943999 (.0000)	1.53E-05 (.3554)
α (ARCH Effect)	0.470470 (.0000)	0.239450 (.0000)	0.582106 (.0000)	0.435449 (.0000)
β (GARCH Effect)	0.607785 (.0000)	0.615681 (.0000)	0.830098 (.0000)	0.617970 (.0000)
Υ(Leverage Effect)	-	0.469723 (.0000)	-0.171781 (.0000)	0.267671 (.0000)
$^{\delta}$(power parameter)	-	-	-	1.937091 (.0000)
$\alpha + \beta$	1.47	.94	1.41	1.05
Log Likelihood	6409.591	6441.740	6447.603	6441.742
SIC	-6.186358	-6.213785	-6.219461	-6.210092
AIC	-6.199991	-6.230145	-6.235821	-6.229179

We have found the presence of a statistically significant risk return relationship only for the EGARCH (1, 1) as indicated by risk premium coefficient in table 3. To confirm the existence of remaining ARCH effects, we have conducted Arch-LM test once again on the residuals of the GARCH models and the p values of this test are given in table 8 of the appendix. The high P values found from this test concludes that all GARCH models used in this research are correctly specified leaving no further ARCH effect to be explained. Moreover, our research states that the asymmetric EGARCH (1, 1) is the best method for modelling volatility dynamics of DGEN index in its pre-crash period as shown by AIC, SIC and Log Likelihood model selection criteria.

CRASH PERIOD

In the crash period, EGARCH (1, 1) and PGARCH (1, 1) confirm statistically significant negative risk return relationship at 5% and 10% levels respectively. We have found significant GARCH coefficients for this sub-period in both symmetric and asymmetric GARCH models. However we have found insignificant ARCH effect only for TGARCH (1, 1). In addition, the sum of ARCH and GARCH coefficients are found close to 1 for all models apart from TGARCH (1, 1) which represents highly persistent shocks on the conditional variance.

Table 4: GARCH models in the Crash Period

Particulars	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)	PGARCH (1,1)
Risk Premium	-0.058580 (.5141)	-0.146293 (.1243)	-0.167714 (.0443)	-0.174215 (.0551)
α_0 (Constant)	7.22E-06 (.0045)	8.48E-06 (.0001)	-0.525912 (.0000)	0.000183 (.5028)
α (ARCH Effect)	0.187034 (.0000)	0.035044 (.2202)	0.263764 (.0000)	0.130411 (.0000)
β (GARCH Effect)	0.808586 (.0000)	0.849158 (.0000)	0.960523 (.0000)	0.855370 (.0000)
ϒ(Leverage Effect)	-	0.187816 (.0000)	-0.118509 (.0000)	0.522797 (.0001)
$^{\delta}$(power parameter)	-		-	1.304081
α + β	0.98	0.87	1.23	0.99
Log Likelihood	1947.039	1958.269	1958.302	1960.057
SIC	-5.246021	-5.267568	-5.267659	-5.263459
AIC	-5.277279	-5.305078	-5.305169	-5.307221

We have found significant Leverage impact at 1% level in all asymmetric GARCH models as exhibited in table 4. In PGARCH (1, 1) model, the optimal power transformation value is significantly different from 1 and 2 at 1% significance level. Further ARCH-LM test conducted on the residuals of the models conclude that apart from the EGARCH (1, 1), all other GARCH models are correctly specified. The p values of the residuals of EGARCH (1, 1) exhibit evidence of remaining un-captured ARCH effects in the model. According to AIC and Log Likelihood model selection criteria, PGARCH (1, 1) is the best model for this selected time frame. On the other hand, we have found contradictory result for SIC criterion as SIC states EGARCH as the best model for the crash period. However considering the results from ARCH-LM test for this period, it is evident that the PGARCH (1, 1) eliminates the ARCH effect better compared to EGARCH (1, 1). Therefore, we have concluded that PGARCH (1, 1) should be the chosen model for crash period in 2010.

POST-CRASH PERIOD

As mentioned earlier, we have taken the post-crash period data from DSEX instead of DGEN. We have found insignificant risk return relationship during this period as indicated by p values of the risk premiums. On the other hand, ARCH and GARCH coefficients are statistically significant in both symmetric and asymmetric GARCH models at 1% level. There are evidences of persistent shocks for all selected models for this period as the collective values of ARCH and GARCH coefficients are really closed to unity. Our leverage impact coefficients captured for all these models are significant at 5% level in contrary to the 1% significance level found in pre-crash and crash periods indicating less persistency compared to other periods.

Table 5: GARCH models in the Post-Crash period

Particulars	GARCH (1,1)	TGARCH (1,1)	EGARCH (1,1)	PGARCH (1,1)
Risk Premium	0.087313 (.5915)	-0.053302 (.7412)	-0.027034 (.8650)	-0.054504 (.7373)
α_0 (Constant)	4.13E-06 (.0302)	3.93E-06 (.0300)	-0.583315 (.0018)	4.54E-07 (.8270)
α (ARCH Effect)	0.147680 (.0000)	0.095851 (.0094)	0.265221 (.0000)	0.128064 (.0000)
β (GARCH Effect)	0.816545 (.0000)	0.824550 (.0000)	0.959892 (.0000)	0.810402 (.0000)
ϒ(Leverage Effect)	-	0.093162 (.0156)	-0.046171 (.0410)	0.161049 (.0486)
$^{\delta}$(power parameter)	-	-	-	2.468837 (.0124)
α + β	.97	.92	1.23	.94
Log Likelihood	1935.048	1937.554	1936.288	1937.647
SIC	-6.418274	-6.415964	-6.411728	-6.405583
AIC	-6.455009	-6.460047	-6.455811	-6.457013

The residual diagnostic Arch-LM test concludes that all GARCH models are correctly specified and no significant ARCH effect is left by these models. The coefficient of power parameter in the PGARCH (1, 1) model is significant at 5% level. According to the Log Likelihood criteria, PGARCH (1, 1) model is the best fitted model in the post-crash period. On the contrary, the values of AIK and SIC signal that TGARCH (1, 1) should be the best model to study the volatility of the DSEX returns at post-crash period.

COMPARISON OF MODEL PARAMETERS

Table 9 shows the percentage changes in model parameters in different sub-periods. From the table we can see that GARCH coefficients have increased for all selected models from pre-crash to crash period. These increases in GARCH coefficients explain that the persistency in the conditional variance has increased from pre-crash to crash period. On the other hand, the rate of change in the conditional variance expressed by ARCH coefficients has decreased in all models from pre-crash to crash period. The leverage coefficients of TGARCH and EGARCH models decrease from pre-crash to cash period whereas the same coefficients increase significantly in the same period for PGARCH model. The changes in GARCH coefficients are not significant from crash to post-crash period. However, the leverage effect exhibited by asymmetric GARCH models used here has decreased significantly from the crash to post-crash period.
Lastly all coefficients considered here have changed significantly from the pre-crash to post-crash period as indicated by the last column of *table 9*.

Table 9: Model differences in different periods

Models	Pre-Crash	Crash	Post-Crash	% change (Pre-Crash to Crash)	% Change (Crash to Post-Crash)	% Change (Pre-Crash to Post-Crash)
ARCH Coefficients						
GARCH (1,1)	0.47047	0.18703	0.14768	-60.2%	-21.0%	-68.6%
TGARCH (1,1)	0.23945	0.03504	0.09585	-85.3%	173.5%	-59.9%
EGARCH(1,1)	0.58211	0.26376	0.26522	-54.6%	0.5%	-54.4%
PGARCH(1,1)	0.43545	0.13041	0.12806	-70.0%	-1.8%	-70.5%
GARCH Coefficients						
GARCH (1,1)	0.60779	0.80859	0.81655	33.0%	0.9%	34.3%
TGARCH (1,1)	0.61568	0.84916	0.82455	37.9%	-2.9%	33.9%
EGARCH(1,1)	0.83010	0.96052	0.95989	15.7%	-0.1%	15.6%
PGARCH(1,1)	0.61797	0.85537	0.81040	38.4%	-5.2%	31.1%
Leverage Coefficients						
TGARCH (1,1)	0.46972	0.18782	0.09316	-60.0%	-50.4%	-80.1%
EGARCH(1,1)	-0.17178	-0.11851	-0.04617	-31.0%	-61.0%	-73.1%
PGARCH(1,1)	0.26767	0.52280	0.16105	95.3%	-69.1%	-39.8%
Power Coefficients						
PGARCH(1,1)	1.93709	1.30408	2.46884	-32.6%	89.3%	27.4%

From table 9, we can thus conclude that the volatility pattern changes for the DSE after 2010 market crash which is evident through changes in parameter coefficients for all three sub-periods.

CONCLUSION

Our research tests four symmetric and asymmetric GARCH models to capture the change in volatility dynamics of DSE due to stock market crash of Bangladesh in 2010. The descriptive statistics calculated for the selected data varies significantly in the pre-crash, crash and post-crash sub-periods. Through these statistics we have shown that our return series exhibit skewness in all three sub-periods. The unit root test shows that the data series is not stationary at level but integrated at first difference for all periods. The ARCH LM-test signifies the presence of ARCH effects and volatility clustering in all sub-periods.

After confirming the presence of ARCH effect, we have tested GARCH models for three sub-periods. In the pre-crash period, positive risk premium offered by the market is confirmed solely by EGARCH (1, 1) model whereas the market exhibit negative risk premium with EGARCH (1, 1) and PGARCH (1, 1) models during crash period. We haven't found significant risk premium in post-crash period. We have found significant ARCH and GARCH coefficients using our selected models for all sub-periods except TGARCH (1, 1) in the crash period. In addition, the asymmetric GARCH models successfully captures the presence of leverage effect in all the sub-periods.

Our research finds a significant shift in volatility pattern due to 2010 market crash. The ARCH, GARCH and Leverage parameter coefficients for all selected models have changed significantly from pre-crash to crash and crash to post-crash period confirming the shift in volatility pattern. Lastly, our research also concludes that compared to the symmetric GARCH (1, 1) model, asymmetric GARCH models perform better at structuring volatility dynamics of the DSE Indices at different market conditions.

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APPENDIX

Figure 1: Closing price of the DGEN index in Pre-Crash and Crash Period

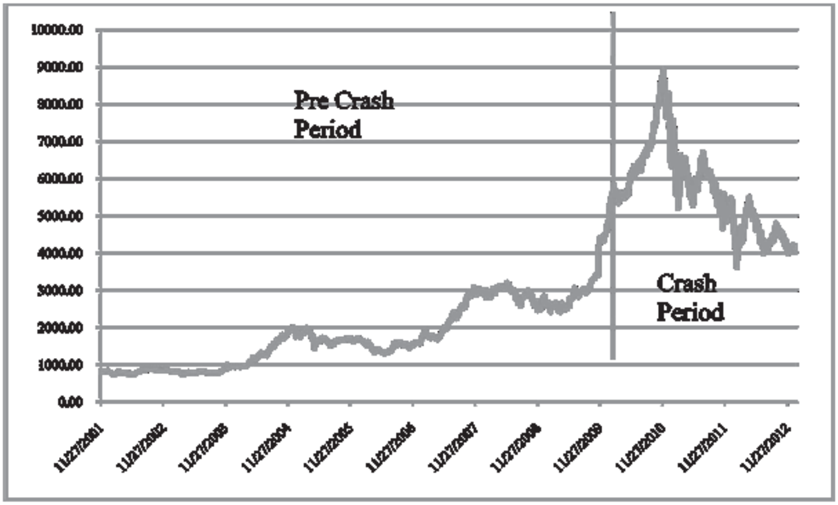

Figure 2: Closing price of the DGEM index in the Post-Crash period

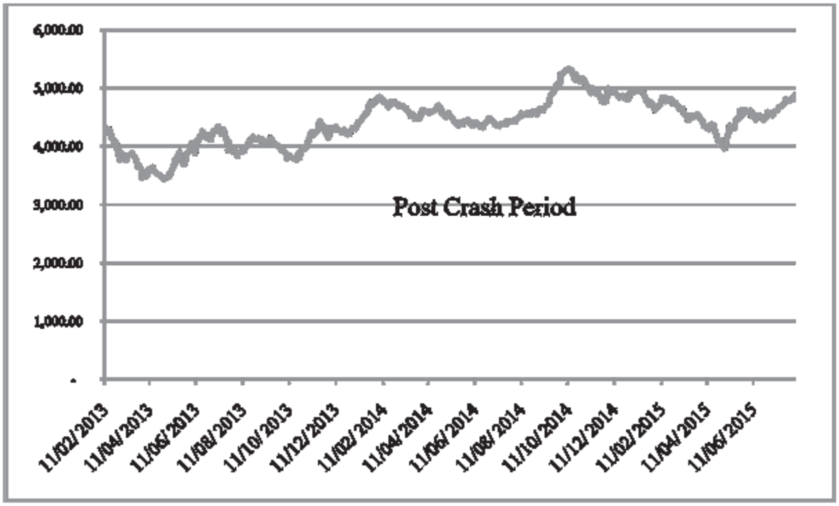

Table 6: ADF UNIT ROOT TEST for General index and return series

	At level				Return Series			
	ADF Statistics	1%	5%	10%	ADF Statistics	1%	5%	10%
Pre-Crash	0.760736	-3.44106	-2.866155	-2.56929	-41.08656	-3.44106	-2.86616	-2.56929
Crash	-1.333922	-3.44106	-2.866155	-2.56929	-27.27876	-3.44106	-2.86616	-2.56929
Post-Crash	-1.26255	-3.44106	-2.866155	-2.56929	-22.65433	-3.44106	-2.86616	-2.56929

Table 7: ARCH LM test for Heteroscedasticity

	Pre-Crash			Crash			Post-Crash			
Lag	1	5	10	1	5	10	1	1	5	10
F Statistics	3.15648 (.0757)	0.96056 (.4407)	0.4867 (.8996)	198.46 (.0000)	43.545 (.0000)	27.955 (.0000)	57.988 (.0000)	57.988 (.0000)	16.141 (.0000)	8.4773 (.0000)
Obs*R Squared	3.1547 (.0758)	4.80560 (.4401)	4.8817 (.8989)	156.60 (.0000)	168.82 (.0000)	204.0656 (.0000)	53.008 (.0000)	53.008 (.0000)	71.663 (.0000)	75.308 (.0000)

Table 8: GARCH models residual diagnostic (for Lag 1 only)

Models	Particulars	Pre-Crash	Crash	Post-Crash
GARCH (1,1)	F Statistics	0.8203	0.1392	0.2529
	Obs*R Squared	0.8201	0.1388	0.2522
TGARCH (1,1)	F Statistics	0.7905	0.3501	0.3107
	Obs*R Squared	0.7904	0.3494	0.3099
EGARCH (1,1)	F Statistics	0.8159	0.0881	0.3998
	Obs*R Squared	0.8158	0.0879	0.399
PGARCH (1,1)	F Statistics	0.7944	0.1309	0.2919
	Obs*R Squared	0.7943	0.1306	0.2911

SHORT INTRODUCTION OF AUTHORS

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