Modeling Returns Volatility of Selected Pharmaceutical Companies Listed in DSE of Bangladesh with GARCH Methods

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ABSTRACT

The main aim of this study is the empirical exploration for the proper volatility models of some selected pharmaceutical companies listed in the DSE, Bangladesh e.g. Square, Beximco, Beacon, IBN SINA, and Orion Pharmaceuticals Ltd. The data covers the 667 days daily log returns calculated based on closing prices of these five selected companies from 28th January 2019 to 30th December 2021. The beginning portion of the analysis contains the stylized facts of the sampled companies. Afterward, by employing both symmetric along with asymmetric GARCH models different best-fitted models for different pharmaceuticals companies were found. Based on our model selection criteria AIC, SBIC, Log-Likelihood, as well as residual diagnostics GARCH(1,1) is considered to be more appropriate models for both Square Pharmaceuticals Ltd., and Beacon Pharmaceuticals Ltd. The EGARCH (1,1) is deemed to be best for both IBN SINA and Orion Pharmaceuticals Ltd. Whereas, anyone of the GARCH(1,1), and TGARCH(1,) can be applied for the volatility estimation of Beximco Pharmaceuticals Ltd.

Keywords: Volatility clustering, Unit root, GARCH, GARCH-M, EGARCH, TGARCH, and Leverage effect.

INTRODUCTION:

Being a thermometer of an economy every capital market reflects the health of any economy. The well-being of every economy largely depends on a vibrant capital market. The growth of new businesses or any economy would not be possible without the availability of equity finance and the advancement of financial markets. The capital markets have a pivotal role in the collection of long-term funds for the deficit unit that wants to invest in the industrial arena.

Hence, a high positive link-up between capital market development and industrial development for every economy exists. But greater capital market volatility may hamper the attractions of the potential investors, which

ultimately a piece of negative news for industrial up-liftment. For Bangladesh, capital market movement is a major concerning issue to the market participants. This market already has witnessed two major debacles e.g. in 1996, and in 2009 within its short history. Hence, capital market movement is a very concerning issue for the market participants in Bangladesh. Individual stock prices or various indices may fall in some situations and maybe constant or rise in another situation. These movements are termed volatility. Such volatility has attracted much concentration of academics, policy-makers, and practitioners during the recent past. In recent years, several models and techniques have been proposed and implemented for

volatility analysis. By proper investigation and prediction, the stock markets can be created as an attractive source of investment. There is extensive usage of Generalized and Autoregressive Conditional Hetero skedasticity- (ARCH & GARCH) family models in modeling and estimating the financial market volatility since their advent. Most of the studies on DSE mainly have focused on all inclusive indices. But, investors and other market participants can find their interests in the movement of particular stocks or industries. A big research gap particularly in modeling the variability of return of any single stock or industry was observed in the case of the financial market of Bangladesh.

Hence, this paper has tried to employ GARCH-type models to deduce the best-fitted model for five selected pharmaceutical firms registered in DSE, Bangladesh e.g. Square Pharmaceuticals Ltd., Beximco Pharmaceuticals Ltd., Beacon Pharmaceuticals Ltd., IBN SINA Pharmaceuticals Ltd, and Orion Pharmaceuticals Ltd.

Literature Review

Market participants, researchers, or academicians are very concerned about the measurement and forecast of the inconstancy of equity returns. The swing of equity prices is very common in almost every exchange within the world. Accurate volatility prediction is important for the market participants for their investment strategy and asset selection. Since its inception, the Bangladesh stock market already witnessed two major debacles in its history i.e. in 1996 and in 2009 and it are familiar as very unpredictable market. So to know about the ways of volatility measurement and forecasting techniques is very essential for the market participants. Several studies tried to capture the irregularity of the stock markets of Bangladesh as follows- Huq and Ali, (2018) studied the variability of the DSE Broad Index (DESX) using the GARCH model. Their study period covers DSEX daily closing index from 27/01/2013 to 04/04/2017. They found GJR-GARCH (1,1) to be the most applicable model volatility prediction. The models' performances were also compared under different statistical error measurement tools. Roni *et al.,* (2017) applied GAR-CH- type models to the Bangladesh stock market. They found that the TGARCH model is more accurate in terms of accuracy. They also found according to the

error measurement statistic that the GARCH is more efficient and has more forecasting ability also. Hasan and Wadud, (2016) tried to search for an adequate volatility model for DSE. They found that MA (1)-EGARCH (1,1) has a leverage effect in current volatility. Their study also discovers that MA (1)-GARCH (1,1) is the finest model for DSE stock returns in Bangladesh. Huq *et al., (*2013) also empirically examined and found GARCH (1,1), and GARCH(2,1) along with ARMA (1,1) as better for DSE. Siddikee and Begum, (2016) applied the GARCH (p, q) and ARCH (m) models to DGEN ranging from 1st January 2002 to 30th July 2013. Their results of the GARCH (1, 1) process and standard deviation corroborated the presence of atypical swings in the returns from 2009 to 2012. Parvez *et al*., (2017) tried to contrast the potentiality of different types of models to forecast the variability of the DSE. They studied 2639 daily observations from 1st January 2002 to 19th June 2012. After comparing the forecasting performances of the twelve models, they found GARCH (1,1) with conditional distribution student-t model as superior in accordance with the RMSE, MAE, Theil-U, and four asymmetric loss functions (Rayhan *et al*., 2011). The main focus of their study is the detection of the pattern and reasons behind the monthly variability of DSE, and to search the possible solutions thereto. They observed a random walk phenomenon in the price index, but not in their returns (Sami *et al*., 2021).

Hossain *et al*., (2012) hunted for a suitable approach for DSE and tried to forecast the future outline of volume data of this market. They selected the ARIMA with the EGARCH model to analyze the volatility as superior. Besides these studies stated above, some studies have tried to correlate the movement of this market along with macroeconomic data. But for individual stocks or specific industries, there has been a big research gap for the Bangladeshi stock market. That's why this paper has tried to employ GARCH-type models in five selected pharmaceuticals limited listed in DSE, Bangladesh.

METHODOLOGY:

Since their invention, ARCH, and its generalization GARCH models had been applied widely in measuring and predicting the variance of markets all over the world. We also employed GARCH-type modelsand

tried to discover the better models for volatility estimation of five selected pharmaceuticals firms' registered in DSE, Bangladesh e.g. Square Pharmaceuticals Ltd., Beximco Pharmaceuticals Ltd., Beacon Pharmaceuticals Ltd., IBN SINA Pharmaceuticals Ltd, and Orion Pharmaceuticals Ltd. We have applied GARCH (1,1), GARCH-M (1,1), EGARCH(1,1), and TGARCH (1,1) models in our investigation. The following section contains a brief explanation.

Modeling Techniques

In our study, we employed four symmetric and asymmetric GARCH approaches. Symmetric GARCH approaches consider past positive and negative information in the same manner. This happens becausetheir variance equations depend onthe extent of lagged residuals and not their signs. But a negative blow can have a larger impact on variance than a similar positive one. Hence in our study, we have employed both types of approaches and tried to recognize the appropriate models for each company based on three commonly used criteria e.g. Akaike information criterion (AIC), Schwarz Bayesian information criterion (BIC), and log-likelihood.

GARCH (1,1) Model

An elementary representation for GARCH (1,1)is as follows-

Mean equation: $\qquad r_t = \omega + \epsilon_t$

Varianceequation: $\qquad \sigma^2{}_t = \alpha_0 + \alpha_1 \epsilon^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1}$

The second equation is termed as variance equation and it has three components: The first component isa constant term, next is the lag squared residuals found from its mean equation, and termed as ARCH. The last one is termed GARCH, which represents the fitted variance from the model during the preceding duration. The conditions are:

$$\alpha_0 \geq 0, \quad \alpha_i \geq 0, \quad \beta_i \geq 0, \quad \alpha_1 + \beta_1 < 1.$$

So, using this approach it is possible to interpret the currently fitted discrepancy as a weighted function of a long-term average value(constant), information about volatility during the previous period(ARCH term), and the fitted variance from the model during the previous period (GARCH term).

The GARCH-in-Mean (GARCH-M) Model

In the mean equation, it is included either variance or standard deviation as the following expression.

Mean equation: $\qquad r_t = \omega + \Upsilon \sigma^2{}_{t-1} + \epsilon_t$

Variance equation: $\qquad \sigma^2{}_t = \alpha_0 + \alpha_1 \epsilon^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1}$

The parameter Υ is recognized as risk premium parameter. A positive Υ specifies that return is positively related to its volatility. Especially, a rise in average return is caused by an increase in conditional variance in the manner that proxy of increased risk.

The Exponential GARCH (EGARCH) Model

Nelson (1991) was the proponent of this approach. Among various ways of expression, one possible specification is given by-

$$Ln(\sigma^2{}_t) = \omega + \beta ln(\sigma^2{}_{t-1}) + \lambda \frac{\mu_{t-1}}{\sqrt{\sigma^2{}_{t-1}}} + \alpha\left[\frac{|\mu_{t-1}|}{\sqrt{\sigma^2{}_{t-1}}} - \sqrt{\frac{2}{\pi}}\right]$$

Where λ is the leverage effect parameter. The significance along with negative values for this parameter ensures the presence of leverage effect in the return. That specifies that good information has a lower impact than negative information to the same extent.

The Threshold Garch (TGARCH) Model

The TGARCH model was introduced by Zakoian, (1994) and Glosten *et al.* (1993). The threshold GARCH (1,1) model specification follows asThe variance equation of TGARCH (1,1) version is:

$$\sigma^2{}_t = \alpha_0 + \alpha_1 \epsilon^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1} + \lambda \epsilon^2{}_{t-1} I_{t-1}$$

Where $I_{t-1} = 1$

If $\epsilon_{t-1} < 0; = 0$ otherwise.

The significant and positive values of λ signify the presence of the leverage effect in the series. The other conditions are: $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$, and $\alpha1 + \lambda \geq 0$.

The Data and Basic Statistics

Data for Analysis

The data comprises 667 days daily ending prices of five selected pharmaceutical companies registered in The Dhaka Stock Exchange Ltd (DSE), Bangladesh from 28th January 2019 to 30th December 2021. These data have been gathered from- https://www.dsebd.org. We have transformed our data into logarithmic daily returns using the following formula:

$$r_t = \log\left(\frac{Pt}{P_{t-1}}\right)$$

The r_t represents the logarithmic daily returns of our sampled companies for time t, Pt is the ending prices of sample companies at time t, P_{t-1} is the corresponding previous days' prices of selected stocks. The descriptive information for all five selected company's returns is exhibited in **Table 1**.

Table 1: Illustrative features of returns.

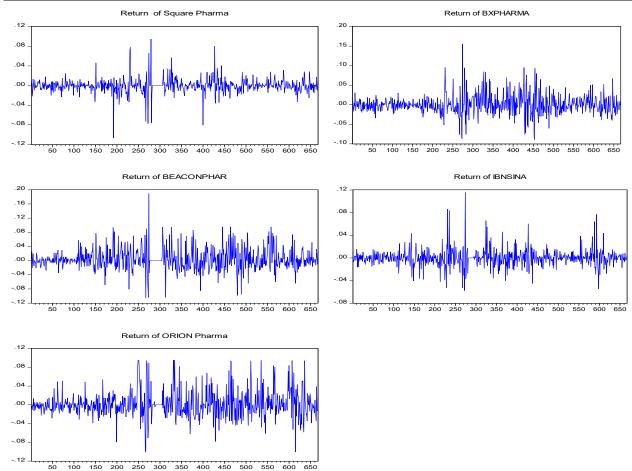|	**SQUR PHARMA**	**BX PHARMA**	**BEACON PHARMA**	**IBN SINA**	**ORION PHARMA**
Mean	-0.00034	0.00118	0.00378	0.00006	0.00129
Median	0.00000	-0.00051	0.00000	0.00000	0.00000
Maximum	0.09452	0.15523	0.18871	0.11559	0.09531
Minimum	-0.10695	-0.08879	-0.10536	-0.05770	-0.10104
Std. Dev.	0.01494	0.02488	0.03039	0.01540	0.02817
Skewness	-0.06956	0.70341	0.63209	1.34537	0.75443
Kurtosis	16.00057	7.27212	6.30770	12.90751	5.43012
Jarque-Bera	4697.73966	562.23100	348.48005	2929.2115	227.39533
Probability	0.00000	0.00000	0.00000	0.00000	0.00000
Sum	-0.22845	0.78493	2.51918	0.04139	0.85871
Sum Sq. Dev.	0.14871	0.41227	0.61523	0.15790	0.52849
Observations	667	667	667	667	667

Fig. 1: Represents the simple line graphs of return data from 28.01.2019 to 30.12.2021 of selected pharmaceutical companies listed in DSE, Bangladesh.

The **Table 1** represents that the distributions of returns of all companies differ markedly from the normality for all companies, observed from watching the skewness figures and excess kurtosis (having value more than 3). Jarque-Bera's pieces of evidence also confirm that normality is rejected at a p-value of almost 1. The

data of five selected pharmaceuticals under review are demonstrated in **Fig. 1**. A return series that contains 'volatility clustering', stimulates to parameterize with an ARCH process. Volatility clustering can be explained as a situation where huge changes within the prices of stocks (of either sign) are taken after by expansive changes, and little changes (of either sign) are taken after by little changes. Such scenarios can be spotted in almost all of the selected pharmaceutical companies from **Fig. 1**.

Testing for Heteroscedasticity

The heteroskedasticity test in the squared residuals can be used to determine whether 'ARCH-effects' are present in the residuals of a predicted method. This test is contingent on the joint null hypothesis that the coefficient values of all q lags of the squared residuals

are not considerably different from zero. The null hypothesis is rejected if the test statistic is greater than the critical value from the $\chi 2$ distribution (Brooks, 2008). By regressing the squared residuals with randomly picked different lags, such as 5,10,15,20, and 25, a check depending upon arbitrarily chosen mean ARMA (1,1) for the presence of ARCH in the residuals is performed. The outcomes presented in **Table 2** showing the probability values with different lags are smaller than even a 1% level of significance for all companies. Hence, there is enough evidence for rejecting the joint null hypothesis, which supports the appearances of 'ARCH'. So the ARCH/GARCH type models can be employed on these return data for proper estimation.

Table 2: The aftereffects of ARCH-LM tests of selected pharmaceuticals companies.

Lags		SQURE PHAR	BX PHAR	BEACON PHAR	IBN SINA	ORION PHARM
5	LM statistic	38.9026	114.1824	39.8017	41.8333	89.4724
	P-Value	0.0000	0.0000	0.0000	0.0000	0.0000
10	LM statistic	48.5766	122.4409	61.6140	50.0136	90.5935
	P-Value	0.0000	0.0000	0.0000	0.0000	0.0000
15	LM statistic	52.7900	122.8676	62.8746	51.9134	94.9862
	P-Value	0.0000	0.0000	0.0000	0.0000	0.0000
20	LM statistic	54.3378	123.5103	64.4438	52.6909	98.9372
	P-Value	0.0001	0.0000	0.0000	0.0001	0.0000
25	LM statistic	54.0200	130.9879	68.0310	52.7914	98.3177
	P-Value	0.0007	0.0000	0.0000	0.0010	0.0000

Testing for Stationarity

Before proceeding for further study it is a prerequisite to know whether the series being dealt with is stationary or not. In such a case, tests like Augmented Dicky-Fuller (ADF, 1988) test and Phillips-Perron (P-P, 1987) test are adopted to test the stationarity of the daily return of all five sampled pharmaceuticals companies. On the log return data series; an augmented Dickey-Fuller (ADF) test was done allowed to 12 lags with three types of equations: an intercept but no trend, trend & intercept, and none.For the same purpose, Phillips-Perron (P-P) test was performed also. There are two hypotheses of consideration; H_0: the data embrace unit root versus H_1: they are stationary. Their outcomes are represented by table 3.0. It is observed clearly that at level, all characters of stats are more negative than the critical values in ADF as well asPP tests in all forms of equations. Again all the probability values are less than even 1% level of significance. So,

based on these analyses our null hypothesiscan strongly be rejected. Hence, all the return data for all five selected pharmaceutical companies are stationary at a level.

Empirical Results

The significant existence of ARCH in residuals of all five sample companies for our study period inspired us to parameterize their returns by applying the following models. All the models performed under the normal Gaussian error distributions. After the model construction, the residual diagnostic check was administered to observe whether there exists any remainder ARCH-effect. The estimated results of all employed models for all the companies i.e. Square Pharmaceuticals, Beximco Pharmaceuticals, Beacon Pharmaceuticals, IBN SINA, and Orion Pharmaceuticals are demonstrated in **Table 4**, **Table 5**, **Table 6**, **Table 7**, and **Table 8** respectively.

Table 3: Results of stationarity tests of daily returns of selected pharmaceutical companies.

Name of Company	Level/ Difference	Test Equation	Augmented Dickey-Fuller Test				Phillips-Perron Test				Comment
			Test-statistic	Critical Value		P-value	T-statistic	Critical Value		P-value	
				1% level	5% level			1% level	5% level		
SQUREPHARMA	Level	Intercept	-24.07	-3.44	-2.87	0.000	-24.05	-3.44	-2.87	0.000	Stationary at level
		Trend & intercept	-24.08	-3.97	-3.41	0.000	-24.06	-3.97	-3.42	0.000	
		None	-24.08	-2.57	-1.94	0.000	-24.06	-2.57	-1.94	0.000	
BX PHARMA	Level	Intercept	-19.78	-3.44	-2.87	0.000	`-24.65	-3.44	-2.87	0.000	Stationary at level
		Trend & intercept	-19.78	-3.97	-3.42	0.000	-24.64	-3.97	-3.42	0.000	
		None	-19.73	-2.57	-1.94	0.000	-24.61	-2.57	-1.94	0.000	
BEACONPHAR	Level	Intercept	-23.99	-3.44	-2.87	0.000	-23.93	-3.44	-2.87	0.000	Stationary at level
		Trend & intercept	-23.98	-3.97	-3.42	0.000	-23.91	-3.97	-3.42	0.000	
		None	-23.67	-2.57	-1.94	0.000	-23.62	-2.57	-1.94	0.000	
IBN SINA	Level	Intercept	-20.68	-3.44	-2.87	0.000	-27.18	-3.43	-2.87	0.000	Stationary at level
		Trend & intercept	-20.69	-3.97	-3.42	0.000	-27.19	-3.97	-3.42	0.000	
		None	-20.69	-2.56	-1.94	0.000	-27.20	-2.57	-1.94	0.000	
ORION PHARM	Level	Intercept	-21.76	-3.43	-2.86	0.000	-21.79	-3.44	-2.87	0.000	Stationary at level
		Trend & intercept	-21.79	-3.97	-3.42	0.000	-21.78	-3.97	-3.42	0.000	
		None	-21.74	-2.57	-1.94	0.000	-21.79	-2.57	-1.94	0.000	
		None	-23.42	-2.57	-1.94	0.000	-23.40	-2.57	-1.94	0.000	

A results summary of different model choosing benchmarks of all estimated models of our five sample companies is also exposed in table 09. With the exception of Beximco, the α_0 (constant) components inside the volatility formulae are seen as being statistically meaningful at the 1%, 5%, and 10% levels in all of our sample companies. For Beximco, this component is significant only for EGARCH (1,1). However, the α_1 (ARCH term), and β_1 (GARCH term) are seen as being statistically relevant at 1%, 5%, and 10%

levels in all models of all our sample companies except only for TGARCH(1,1) of Beacon Pharmaceuticals. Where β_1 (GARCH term) isn't observed as statistically significant. The significance of these ARCH, as well as GARCH components imply that their lagged variance together with lagged squared disturbance have impacts on today's conditional variance. So their previous volatilities have explanatory power on present volatilities for all companies.

Table 4: Expresses the findings of various GARCH approaches for the Square Pharmaceuticals Ltd.

Coefficients	GARCH (1,1)	GARCH-M (1,1)	EGARCH (1,1)	TGARCH (1,1)
Mean Equation				
ω	-0.00073	-0.000801	-0.00115**	-0.00085
Ƴ (risk premium)		0.44044		
Variance Equation				
α_0 (constant)	1.72e-05***	1.71e-05***	-0.94578***	1.73e-05***
α_1 (ARCH term)	0.2335***	0.23259***	0.33651***	0.19305***
β_1 (GARCH term)	0.7394***	0.74011***	0.91486***	0.74078***
λ_1 (leverage term)			0.00963	0.08118***
$\alpha_1 + \beta_1$	0.9729	0.9727	1.2514	0.93383
AIC	-5.7665	-5.7636	-5.7719	-5.7660
SBIC	-5.7395	-5.7298	-5.7381	-5.7323
Log likelihood	1927.14	1927.15	1929.92	1927.97
ARCH-LM Test for Heteroscedasticity (with lag 5)				
Statistic	1.5874	1.59085	1.6799	1.68252
Probability	0.9028	0.9024	0.8914	0.8911

Remark: ***, **, * represents significant at 1%, 5% and 10% level respectively.

The outcomes of the variance equation shown in the **Table 4** justify that the initial three coefficients α_0 (constant), α_1 (ARCH term), and β_1 (GARCH term) are significant. The relevance of the ARCH as well as GARCH elements in GARCH (1,1) suggests that the variance is affected by lagged conditional volatility and squared disturbances. The meaning of that is the past volatility has illustrative power for present volatility. The score of the two estimated ARCH, & GARCH coefficients; $\alpha_1 + \beta_1$ in our beginning model is close to one, indicating that volatility shocks are quite persistent (Abdalla, 2012). The consequence of shocks seems not to be dried out. The GARCH-M (1,1) model considers variance in its mean equation in case of estimation. From estimation results in **Table 4**, the estimated coefficient Υ (risk premium) of σ^2 is seen to be positive and not significant. But such inclusion might be helpful for the significance of the GARCH factor in variance equation. Again, to observe the appearance of leverage effect in data of Square Pharmaceuticals Ltd. we applied EGARCH (1,1), & TGARCH (1,1) models. The λ_1 (leverage term) for the EGARCH (1,1) shows a positive and statistically not significant value, indicating no vicinity of such effect. In TGA-RCH (1,1) estimation results the leverage term is positive in conjunction with significant. The significance of this coefficient ensures the existence of such an effect, which implies that negative shocks can substantially affect the volatility of this firm compared to a positive one. The findings of diagnostic tests for Heteroscedasticity (with lag 5) are displayed in the ending area on **Table 4**. The ARCH-LM test statistics for all models aren't found as statistically significant; which assures that these models don't exhibit additional ARCH effects in their residuals. Despite the fact that the asymmetric term is not found to be significant for EGARCH (1,1), our model choosing criterion AIC having the lowest value (-5.7719), and Log-likelihood with its highest value (1929.92) selects this as a better model for Square Pharmaceuticals Ltd. But after the construction of this model still, serial correlation is noticed in residuals. On the contrary, the criterion SBIC with its lower most figure (-5.7395), finds GAR-CH(1,1) as best, and no serial correlation found in the result of residuals diagnostic check up to 36 lags under this model. So between the two above selected approaches GARCH (1,1) can be considered as best for this company.

Table 5: shows the findings of various GARCH-type models for Beximco Pharmaceuticals Ltd.

Coefficients	GARCH(1,1)	GARCH-M(1,1)	EGARCH(1,1)	TGARCH (1,1)
Mean Equation				
ω	0.00027	-0.000563	-2.51e-05	-8.57e-05
Υ (risk premium)		3.057918		
Variance Equation				
α_0 (constant)	4.87e-06	5.12e-06	-0.35604***	3.12e-06
α_1 (ARCH term)	0.16414***	0.163005***	0.29840***	0.11023***
β_1 (GARCH term)	0.84279***	0.84265***	0.98343***	0.86401***
λ_1 (leverage term)			-0.03003	0.07844**
$\alpha_1 + \beta1$	1.00693	1.007	1.282	0.97424
AIC	-4.9483	-4.9502	-4.9526	-4.9529
SBIC	-4.9213	-4.9164	-4.9189	-4.9191
Log likelihood	1654.26	1655.88	1656.71	1656.79
ARCH-LM Test for Heteroscedasticity(with lag 5)				
Statistic	1.5874	5.6823	5.52068	4.62379
Probability	0.9028	0.3384	0.3557	0.4635

Remark: ***, **, * represents significant at 1%, 5% and 10% level respectively.

Table 5 represents the results for Beximco Pharmaceuticals Ltd. The figures for the second equation show that α_1 (ARCH) including β_1 (GARCH) are statistically significant. The α_0 (constant) isrecognized as significant only for EGARCH (1,1). The relevance of the ARCH, as well as GARCH elements in GARCH (1,1), suggests that the variance is affected by lagged conditional volatility and squared disturbances. The meaning of that is the past volatility has illustrative power for present volatility. Moreover, the score of the two estimated ARCH, & GARCH coefficients; $\alpha_1 + \beta_1$ in our beginning model is is greater than one (1.00065)

representing the volatility process as explosive (Abdalla & Winker, 2012). So, the consequences of shocks will never dry out. The GARCH-M (1,1) model considers variance in its mean equation in the regard of estimation. In estimation results in **Table 5**, the estimated coefficient Υ (risk premium) of σ^2 is seen to be positive and not significant. But such inclusion might be helpful for the significance of the GAR-CH factor in variance equation. No feedback comes from the variance after the inclusion of its mean equation. The λ_1 (leverage term) for the EGARCH (1,1) shows a negative but statistically not significant value, indicating no leverage effect. In TGARCH (1,1) the coefficient of this component is positive in addition to significant, meaning that bad news will have a bigger impact in its conditional volatility than good news. The diagnostic tests for Heteroscedasticity city (with lag 5) are also reported in **Table 5**. The LM statistics for all models cannot be located as statistically significant; which assures that these models don't exhibit additional ARCH effects in their residuals. These prove that the variance equations have been properly specified. However, AIC having the lowest value (-4.9529), and Log-likelihood with its highest value (1656.79) select the same approach i.e. TGARCH (1,1) as the best-fitted model for Beximco Pharmaceuticals Ltd. Whereas, SBIC having the lowest value(-4.9213), finds GARCH (1,1) as best. Again, after applying both TGARCH (1,1), and GARCH(1,1) no serial correlation in residuals was detected up to 36 lag.

Table 6: represents the findings of various GARCH-type models for Beacon Pharmaceuticals Ltd.

Coefficients	GARCH(1,1)	GARCH-M(1,1)	EGARCH(1,1)	TGARCH (1,1)
Mean Equation				
ω	0.00272***	0.001631	0.00354	0.002885***
Υ (risk premium)		1.912379		
Variance Equation				
α_0 (constant)	5.90e-06***	5.96e-06***	-0.17140***	5.69e-06***
α_1 (ARCH term)	0.075637***	0.07602***	0.09748***	0.09009***
β_1 (GARCH term)	0.922640***	0.92216***	0.98583***	0.92475
λ_1 (leverage term)			0.05708***	-0.03989*
$\alpha_1 + \beta_1$	0.9983	0.99818	1.0833	1.015
AIC	-4.3322	-4.3310	-4.3362	-4.3329
SBIC	-4.3052	-4.2973	-4.3024	-4.2992
Log likelihood	1448.80	1449.40	1451.11	1450.04
ARCH-LM Test for Heteroscedasticity(with lag 5)				
Statistic	3.0365	3.1444	6.57234	2.60478
Probability	0.6944	0.6777	0.2544	0.7606

Remark: ***, **, * represents significant at 1%, 5% and 10% level respectively.

Table 6 represents Beacon Pharmaceuticals Ltd. Under all of the methods, the outcomes for the variance equation find the α_0 (constant), as well as the α_1 (ARCH) as significant. Whereas, the β_1 (GARCH) is significant except for TGARCH (1,1).The relevance of the ARCH, as well as GARCH factors in GAR-CH(1,1), suggests that the variance is affected by lagged conditional volatility and squared disturbances. The meaning of that is the past volatility has illustrative power for present volatility. The sums of ARCH plus GARCH coefficients; $\alpha_1 + \beta_1$ in all the GARCH-type models are in the vicinity of, or higher than one, which implies that shocks are roughly persistent and wouldn't become dry out. The GARCH-M (1,1) model considers variance in its mean equation for assessment. The GARCH-M (1,1) model considers variance in its mean equation in the event of estimation. In estimation results in table 06, the estimated coefficient Υ (risk premium) of σ^2 is seen to be positive and not significant. So, no feedback comes from the variance after inclusion of it in mean equation for Beacon Pharmaceuticals Ltd. The λ_1 (leverage term) for the EGARCH (1,1) indicates a non-negative but statistically significant value, indicating no existence of such effect. In TGARCH (1,1) the digit of the leverage factor is negative as well as significant with only at 10% level,

which also supports the non-existence of this effect. The diagnostic tests for Heteroscedasticity (with lag 5), demonstrate that the test statistics for almost all methods are not statistically significant. So, no remaining ARCH exists in residuals of the above models. The criteria AIC having the lowest value (-4.3362), and Log-likelihood with its highest value (1451.11) select the same i.e. EGARCH (1,1) as the best-fitted model

for Beacon Pharmaceuticals Ltd. Whereas, SBIC having lowest value (-4.3052), finds GARCH(1,1) as best. The residuals of EGARCH(1,1) contain serial correlation. On the contrary, in the event of GARCH (1,1), we didn't find any serial correlation after construction up to 36 lags. So, the GARCH(1,1) selected by SBIC appears to be a better model for Beacon Pharmaceuticals Ltd.

Table 7: presents the findings of various GARCH-type models for IBN SINA Pharmaceuticals Ltd.

Coefficients	GARCH(1,1)	GARCH-M(1,1)	EGARCH(1,1)	TGARCH (1,1)
Mean Equation				
ω	0.000156	0.000302	0.000155	1.10E-05
Υ (risk premium)		-1.141490		
Variance Equation				
α_0 (constant)	9.71e-06***	9.68e-06***	-0.80954***	9.39e-06***
α_1 (ARCH term)	0.2270***	0.22881***	0.38421***	0.181384***
β_1 (GARCH term)	0.7646***	0.76391***	0.93711***	0.771082***
λ_1 (leverage term)			-0.01861	0.080988**
$\alpha_1 + \beta_1$	0.9916	0.99272	1.321	0.952466
AIC	-5.8192	-5.8165	-5.8291	-5.8188
SBIC	-5.7922	-5.7828	-5.7953	-5.7851
Log likelihood	1944.71	1944.81	1949.00	1945.58
ARCH-LM Test for Heteroscedasticity(with lag 5)				
Statistic	4.9856	5.1011	5.58402	5.6655
Probability	0.4176	0.4037	0.3488	0.3401

Remark: ***, **, * represents significant at 1%, 5% and 10% level respectively.

Table 7 represents IBN SINA Pharmaceuticals Ltd. The first three coefficients of the variance equation are acknowledged as significant. The relevance of the ARC, as well as GARCH factors in GARCH (1,1), suggests that the variance is affected by lagged conditional volatility and squared disturbances. The meaning of that is the past volatility has illustrative power for present volatility. The sums of ARCH plus GARCH coefficients; $\alpha_1 + \beta_1$ in all the GARCH-type models are in the vicinity of, or higher than one, which implies that shocks are roughly persistent and wouldn't become dry out. The GARCH-M (1,1) model considers variance in its mean equation for assessment. The GARCH-M (1,1) model considers variance in its mean equation in the event of estimation. In estimation results in **Table 7**, the estimated coefficient Υ (risk premium) of σ^2 is seen to be positive and not significant. So, no feedback comes from the variance after inclusion of it in mean equation for IBN SINA Pharmaceuticals Ltd. The λ_1 (leverage effect) for the EGA-

RCH (1,1) shows a negative but statistically not significant value, indicating the non-existence of such effect in data. In TGARCH (1,1) the asymmetry term is positive together with significant with 5% & 10% levels, which advocates in favor of the existence of such effect. This implies that negative shocks can substantially affect the volatility of this firm compared to a positive one. The diagnostic tests for Heteroscedasticity (with lag 5), recognize that the test statistics for all methods are not statistically significant. So, no remaining ARCH exists in residuals of the above models. However, each of the two criteria AIC,& SBIC having their respective minimum values (-5.8291),& (-5.7953) select EGARCH(1,1) as the best-fitted model for IBN SINA Pharmaceuticals Ltd. Log-likelihood with its highest value (1949.00) also select the same volatility prediction model for this company. The serial correlation diagnostic also produces the desirable findings for EGARCH (1,1).

Table 8: contains the findings of various GARCH-type models for Orion Pharmaceuticals Ltd.

Coefficients	GARCH(1,1)	GARCH-M(1,1)	EGARCH(1,1)	TGARCH (1,1)
Mean Equation				
ω	-0.000191	-0.00148	-0.00024	-8.56e-05
ϒ (risk premium)		2.56194		
Variance Equation				
α_0 (constant)	3.74e-05***	3.68e-05***	-0.57684***	3.39e-05***
α_1 (ARCH term)	0.1913***	0.18879***	0.22930***	0.20384***
β_1 (GARCH term)	0.7788***	0.78146***	0.94449***	0.80207***
λ_1 (leverage term)			0.08354***	-0.085757*
$\alpha_1 + \beta_1$	0.9701	0.97025	1.1738	1.0059
AIC	-4.5382	-4.5383	-4.5740	-4.5387
SBIC	-4.5112	-4.5045	-4.5402	-4.5050
Log likelihood	1517.49	1518.51	1530.42	1518.67
ARCH-LM Test for Heteroscedasticity(with lag 5)				
Statistic	1.2934	1.41659	6.2599	1.54031
Probability	0.9356	0.9225	0.2817	0.9084

Remark: ***, **, * represents significant at the 1%, 5% and 10% level respectively.

Table 8 represents Orion Pharmaceuticals Ltd. The first three coefficients of the variance equation were observed as significant. The relevance of the ARCH, as well as GARCH factors in GARCH (1,1), suggests that the variance is affected by lagged conditional volatility and squared disturbances. The meaning of that is that past volatility has illustrative power for present volatility. The sums of ARCH plus GARCH coefficients; $\alpha_1 + \beta_1$ in all the GARCH-type models are very near to, or higher than one, which implies that shocks are roughly persistent and wouldn't become dry out. The GARCH-M (1,1) model considers variance in its mean equation for assessment.

In estimation results in **Table 8**, the estimated co-efficient ϒ (risk premium) of σ^2 is seen to be positive and not significant. So, no feedback comes from the variance after including of it in mean equation for Orion Pharmaceuticals Ltd. The λ_1 (asymmetry term) for the EGARCH (1,1) indicates a non-negative and statistically significant value, indicating the non-existence of the leverage issue. For TGARCH (1,1) the leverage factor is negative together with significant with only at 10% level, which also admits the non-existence of such effect in the data. The diagnostic tests for Heteroscedasticity (with lag 5), illustrate that the test statistics for all approaches are not statistically significant. So, no remaining ARCH exists in residuals of the above models.

However, each of the two criteria AIC & SBIC having their respective minimum values (-4.5740), & (-4.5402) select EGAR-CH(1,1) as the best-fitted model for Orion Pharmaceuticals Ltd. Log-likelihood with its highest value (1530.42) also select the same volatility estimation model for this company. The serial correlation diagnostic also furnishes the desirable outcomes for EGARCH(1,1).

Table 9: shows the summary of the best-fitted models for all five sampled companies.

Name of Company	AIC	SBIC	Log Likelihood	More Appropriate
Square Pharma	EGARCH(1,1)	GARCH(1,1)	EGARCH(1,1)	GARCH(1,1)
BeximcoPharma	TGARCH(1,1)	GARCH(1,1)	TGARCH(1,1)	Anyone
Beacon Pharma	EGARCH(1,1)	GARCH(1,1)	EGARCH(1,1)	GARCH(1,1)
IBN SINA	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	-
Orion Pharma	EGARCH(1,1)	EGARCH(1,1)	EGARCH(1,1)	-

CONCLUSION:

The main thirst of this piece of research is the empirical investigation of the approximation of the volatility of a few pharmaceutical companies registered in DSE, Bangladesh. The first part of this manuscript contains the summary stats of the sampled companies. Afterward, by employing GARCH-type methods we found different best-fitted models for different pharmaceuticals companies. **Table 9** shows that in reliance on AIC, and Log-Likelihood, EGARCH (1,1) was turned out to be the best-fitted model for every single company except for Beximco Pharmaceuticals Ltd. For this firm TGARCH (1,1) is appeared to be best by them. Conversely, SBIC finds GARCH (1,1) as a superior method in each of the following three companies i.e. Square Pharmaceuticals Ltd., Beximco Pharmaceuticals Ltd., and Beacon Pharmaceuticals Ltd. Whereas, the EGARCH (1,1) in each of the two firms i.e. IBN SINA and Orion Pharmaceuticals Ltd. have been appeared to be a better approach depending on SBIC criterion. Lastly, the EGARCH (1,1) has been accepted as superior for all the companies except Beximco Pharmaceuticals Ltd. For this firm TGARCH (1,1) has been accepted by this criterion. Despite the fact that EGARCH (1,1) was chosen as the prediction fits for both Square Pharmaceuticals and Beacon Pharmaceuticals relying on their AIC and Log-likelihood values, the residuals diagnostic checks revealed the serial correlations. Hence, GARCH (1,1) selected by SBIC appears to be superior for each of these two companies. However, there are only limitations for all selected methods for the above companies that their residuals weren't proved to be normally distributed even after employing the models. But still, the models can be implemented as they have passed their other two residual diagnostics e.g. non-existence of Arch, and serial correlation. Actually, stock market movement is a general aspect of any share market. In occupancy of high return volatility, potential investors lose interest to invest in such a market. Political unrest and man-made crisis sometimes create the share market more unstable. Hence, investors need to be aware of the disposition of risks involved in a particular stock or in a specific sector. This paper would be helpful to know these, and thus obviously to take their appropriate decisions.

CONFLICTS OF INTEREST:

The authors want to declare that there is no conflict of interest with any bodyregarding this research work.

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