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Stock Price Volatility: An Empirical Investigation of Some Selected Securities in the Chittagong Stock Exchange

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Abstract

This paper examines the volatility of share prices and potential asymmetric effect of good and bad news on volatility in the stock market of Bangladesh. Using 2,615 daily observations on share prices of six commercial banks each, of the period from December 2011 to January 2021, we examine the existence of ARCH effect and then estimate ARCH model. GARCH model has been estimated and found more suitable for modeling and forecasting the volatility in share market. In order to examine whether bad news in the share market causes more turbulence, we have estimated the Threshold GARCH model. Estimation outputs of TGARCH model do not provide any evidence of asymmetry in the impact of good or bad news on share prices because the threshold dummy of the estimated TGARCH model is found insignificant for all banks' share prices. The findings of our research have important implication for the investors seeking portfolio investment as well as for the financial market analysts.

Keywords: Volatility, Asymmetric effect, Forecasting, ARCH, GARCH, TGARCH, Portfolio investment

1. Introduction

Volatility in stock market refers to the fluctuation of share prices over a period of time. This definition follows Bukenya (2017), who in his paper presented a general definition of volatility. Balaban et al. (2006) defines volatility as within-month standard deviation of continuously compounded daily returns on the stock market index. High volatility in share prices most often discourages the general investors to involve in or stay with the stock market. A drastic fall or rise in stock price has adverse impact on the mindset of the participants. This form of volatility erodes public confidence and gradually market participants leave the market which might

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permanently jeopardize the investment climate of an economy. Bangladesh has experienced several extreme forms of stock market volatility in 1996, 2010 and 2017. These steep swings that occurred in 1996 and 2010 ultimately came to be known as stock market crashes. However, the volatility of 2017 continued for a longer period but it did not lead to market crash. Recent spread of COVID-19 invited further catastrophe to the stock market. Until recently, from the middle of 2019 there appears an uptrend in share index. It has been observed that volatile share market mostly benefited the large investors because sensing further fall in stock price they use to sell off their shares and leave the market with huge profit, keeping the small investors in the situation of sharp price fall with many losing their capital (Islam and Ahmed, 2015).

Economic development of a country greatly depends on the strength and soundness of its equity market. People in Bangladesh having savings look for safe and profitable mode of investment. One promising hub of investment could have been the stock market because banks and other depository organizations currently offer very small rate of profit or interest. But stock market could not attract the capital owners because of its inherent volatility. Lack of confidence and knowledge made the stock market of Bangladesh inefficient in terms of investing as well as disinvesting. Watching sudden increase in stock prices, many investors buy shares but instead of staying longer, they leave market as soon as a drop in stock price occurs. Correct assessment of volatility and forecasting is likely to help the investors invest in share market. According to Stanciu (2009), the ability to forecast financial market volatility is important for portfolio selection and asset management.

Our current research is designed to model the volatility in share prices and examine whether the nature of volatility is dynamically explosive or convergent. We have analyzed the data of share prices of six commercial banks. Choice of banks as the company lies in the fact that general public believe buying banks’ shares would be less risky as the banks are assumed to have well-organized physical, financial and administrative structure. Empirical measure of risk requires the application of autoregressive conditional heteroskedastic (ARCH) class of models. Using about ten years’ daily data, we firstly investigate the presence of ARCH effects. Suitability of ARCH and GARCH models in estimating the dynamic variances of share prices has been assessed. In general, it is expected that increase in share prices would be a good news to the investors and therefore the degree of volatility would be lesser than what would be if share prices decrease. Such asymmetric effect of shocks on volatility has been examined by estimating threshold GARCH (TGARCH) model.

The paper is organized as follows. The second section reviews the existing literature related to stock market volatility. Source of data and methodology used in the paper are presented in the third section. The fourth section illustrates empirical results. Some concluding remarks are documented in the final section.

2. Literature Review

A good number of papers investigating stock market volatility around the world have been written but very few papers focused on the stock market of Bangladesh. Henry (1995) used daily data from the Hong Kong Stock Exchange to model stock market volatility. The author obtained several contrasting results by employing a partially nonparametric model to examine the relationship between shocks and volatility.

Using monthly data from 1976 to 1994, Choudhry (1996) investigated the volatility of stock markets of six countries. The research found the existence of volatility. However, Bangladesh was not one of the sample countries. Furthermore, asymmetric or leverage effect of shocks has not been addressed. Koutmos (1998) estimated threshold GARCH model for nine stock markets and found the evidence of leverage effect which refers to disproportionate impact of past innovations on the conditional variance.

Husain and Uppal (1999) examined stock returns volatility in the Pakistani equity market. According to their findings, GARCH(1,1) is an appropriate representation of conditional variance, implying that current volatility in the market is significantly affected by the past volatilities.

Bekaert and Wu (2000) highlighted the leverage effect and volatility feedback effect in explaining asymmetrical volatility in response to good and bad news channeled in the equity market. Onur (2001) investigated the volatility in Saudi stock market and concluded that abnormal swings in stock prices may be reduced by regulating bank credits to private sector.

Mishkin and White (2002) observed the volatility in stock market due mainly to the negligence of regulatory authority and lack of knowledge of the investors who expect profit within short duration of times. The survey, in the context of Romanian Stock Market, carried out by Stanciu (2009) also supports the leverage effect of asymmetric volatility. Estimating TGARCH model by using daily observations for the period from 1998 to

2008, the paper concluded that good and bad news of the same magnitude in the stock market have different impacts on the volatility level.

James and Karoglou (2009) looked into the stock market volatility in Indonesia. One of the major findings of their research was substantial fall in stock volatility through foreign participation. Singh and Makkar (2014) applied GARCH model to establish the relationship between stock returns volatility and financial crisis. Eryilmaz (2015) viewed the stock market volatility as a marker of inefficient pricing of stock shares and insufficient functionality of the financial market.

Authors around the world carried out adequate amount of surveys highlighting the stock market volatility. Returns from stocks largely depend on the unforeseeable volatility and thereby estimating market price volatility with high degree precision remains as an interesting area of research. Unlike many other markets all over the world, the stock market in Bangladesh experiences frequent swings, which signifies the existence of structural breaks in terms of time horizon. We therefore attempt to include time dummies to estimate time-dependent mean share prices. Significance of time dummy variables would justify the variation of share prices at different clusters of time. To the best of our knowledge, no such study has been undertaken for estimating significantly different mean share price of the same stock. Moreover, asymmetric effect of shocks on time varying volatility of share price is a fundamental feature. Extant literatures suggest that the shock generated through the fall in share price will cause more volatility than the shock emerged through the rise in share price. Asymmetric effect of shocks on volatility has not been examined by many authors using data from Stock Exchanges in Bangladesh. We could retrieve only one paper authored by Hasan (2017) who found the evidence of diverse intensity of good and bad news in the share market. We use latest dataset to check the robustness of asymmetric effect.

3. Data and Methodology

A total of 2,615 daily observations on share prices of six commercial banks, each starting from January 2010 until January 2021, have been retrieved online from the website of the Chittagong Stock Exchange. Day-end closing price has been considered as the share price. In case of unavailability of closing price on a certain date, the previous day's closing price has been taken for account. Six banks are respectively Al Arafah Islami Bank, Bank Asia, BRAC Bank, Islami Bank Bangladesh Ltd (IBBL), Pubali Bank and Rupali Bank. Of the sample banks, two are

Islamic Shariah-based banks, three are conventional commercial banks and one is nationalized commercial bank. Out of 2,615 daily observations, we carried out empirical investigation basing on 2,155 observations because there occurs heterogeneity in the face values of shares as the companies revised the face values of respective stocks around December 2011.

Figure 1: Dynamics of Share Price

Source: Diagram Produced using Data from Chittagong Stock Exchange

Main objective of our research is to investigate the volatility of share price, which is the source of potential risk. Figure 1 helps understand the possible volatility in share prices of sample banks.

In order to measure the volatility, we begin with the simplest form of a model having AR(1) error term.

$$y_t = \psi + e_t \qquad .... \qquad (1)$$

$$e_t = \rho e_{t-1} + v_t \;\; ; \;\; |\rho| < 1 \quad .... \quad (2)$$

Here, y_t represents share price, and v_t is assumed to be normally distributed with zero mean and constant variance $\left(\sigma_v^2\right)$. The unconditional mean and variance of the error term are 0 and $\frac{\sigma_v^2}{1-\rho^2}$ respectively. However, the conditional (conditional upon the information until previous period) mean and variance are ρe_{t-1} and σ_v^2 respectively. Conditional variance (σ_v^2) is smaller than unconditional variance $\left(\frac{\sigma_v^2}{1-\rho^2}\right)$. This suggests that the degree of precision improves through conditioning. Here, the conditional variance appears to be constant but in real life situation variance changes over time.

This feature is introduced by assuming a dynamic variance of the error term, B_t. Let the dynamic variance is

$$B_t = \gamma_0 + \gamma_1 e_{t-1}^2, \quad \gamma_0 > 0, \quad 0 \le \gamma_1 < 1 \quad .... \qquad (3)$$

This follows, $e_t \sim N(0, B_t)$

The above formulation, through introducing dynamic variance, characterizes autoregressive conditional heteroskedastic (ARCH) class of models (Engle, 1982). Such models are very popular because they can capture the stylized features of real life volatility. Volatility is the fluctuation in economic variable over a period of time.

Under the specification characterized by equation (3), we can forecast the volatility of share price (*y*) at time *t* by knowing the previous period's error (e_{t-1}). In financial time series analysis, the errors are termed as "shocks" or "news". In our present research, positive shock refers to the increase, and negative shock decrease in share price. ARCH models can explain the volatility as a function of the shocks. Using these shocks, estimation of the dynamic variance is done to assess the risk. The effect of shocks on the volatility is popularly known as ARCH effect. Presence of ARCH effect signifies the time varying volatility.

ARCH effect is investigated by using Lagrangian multiplier (LM) test. Steps are as follows. Firstly residuals are computed by estimating equation (1): $y_t = \psi + e_t$; where, y stands for share price and ψ is a constant. In the second step, squared residuals are regressed on lagged squared residuals. Construction of the test follows:

$$\hat{e}_t^2 = \omega_0 + \omega_1 \hat{e}_{t-1}^2 + \Psi_t \quad .... \qquad (4)$$

Corresponding null and alternative hypotheses are $H_0 : \omega_1 = 0$ and $H_A : \omega_1 \neq 0$

LM Test statistic: $(T\text{-}q)R^2$

Here T is the sample size and q is the number of lags.

If $(T - q)R^2 \ge \chi^2_{(1-\alpha, q)}$ then reject null hypothesis and conclude that ARCH effects are present.

We further examined market volatility by forming separate clusters of periods with the objective of checking time varying mean as well as variance. Several time dummy variables have been introduced to capture the time-dependent mean of share prices. Residuals obtained from the estimation of the dummy-augmented mean equation have been used to test for ARCH effects.

If ARCH effects are found to be present then we estimate ARCH models. Maximum likelihood (ML) method is more appropriate to estimate ARCH models.

ARCH(1) model can be extended by taking lags up to period *q*, and the converted model is called ARCH(q) model. Equation (5) represents the general form of ARCH(q) specification.

$$B_t = \gamma_0 + \gamma_1 e_{t-1}^2 + \gamma_2 e_{t-2}^2 + \gamma_3 e_{t-3}^2 \,..... + \gamma_q e_{t-q}^2 \qquad .... \qquad (5)$$

Estimation of ARCH(q) model becomes complicated while considering so many lags. The problem can be solved by estimating corresponding generalized ARCH or GARCH model (Bollerslev, 1986).

Manipulation of the ARCH(q) model yields the following GARCH(1,1) model with only three parameters.

$$B_t = \phi + \gamma_1 e_{t-1}^2 + \alpha_1 B_{t-1} \qquad .... \qquad (6)$$

In the presence of *p* lags in *B* and *q* lags in e^2, the model is named GARCH(*p*,*q*) model. In this study, we used the GARCH(1,1) model to measure the extent of share price volatility.
If $\gamma_1 + \alpha_1 < 1$, GARCH is stationary, otherwise integrated.

Popularity of GARCH model stems from the fact of requiring only few parameters to be estimated while being able to substantially capture the real life features.

Standard ARCH model reflects symmetric effect of previous period's shocks on the volatility. For example, in the variance equation $B_t = \phi + \gamma_1 e_{t-1}^2 + \alpha_1 B_{t-1}$, the impact of e_{t-1}^2 on B_t is γ_1, no matter how e_t is- it may be positive or negative. But a negative shock ($e_{t-1}<0$) in share market invites extreme turbulence compared to a positive shock ($e_{t-1}>0$). Such reality calls for the consideration of asymmetric effect. Threshold GARCH (TGARCH) model of the following form is able to capture the asymmetric effect of good news and bad news on volatility.

$$B_t = \phi + \gamma_1 e_{t-1}^2 + \delta d_{t-1} e_{t-1}^2 + \alpha_1 B_{t-1} \qquad .... \qquad (7)$$

Here, d_t works as a dummy variable.

$d_t=0$, when good news comes up ($e_t > 0$) and $d_t=1$ when bad news emerges ($e_t < 0$).

For share market example, good news means the occurrence of higher share price than the estimated price, which causes γ_1 unit change in volatility due to one unit change in e_{t-1}^2. When bad news transmits, the change in volatility would be $\gamma_1 + \delta$. A significant δ justifies the asymmetric impact of the shocks on volatility. We have examined the asymmetric effect of shocks by estimating the TGARCH model.

4. Empirical Results

Tests for ARCH effects on the share prices of six banks have been carried out in the first step for the specification and selection of the model. The ARCH – Lagrange multiplier (LM) test results are presented in Table 1. Test equations follow $y_t = \psi + e_t$ and $\hat{e}_t^2 = \omega_0 + \omega_1 \hat{e}_{t-1}^2 + \Psi_t$

Table 1: Testing the Presence of ARCH Effects

Banks	Estimate of the constant $(\hat{\psi})$	Computed value of LM test statistic $(T\text{-}q)R^2$	5% Critical value of test statistic $(\chi^2_{(0.95,1)})$	ARCH effects
Al Arafah Bank	18.98 (0.00)	2109.94	3.841	Present
Bank Asia	18.97 (0.00)	2103.98		Present
BRAC Bank	66.73 (0.00)	2114.95		Present
IBBL	25.66 (0.00)	2113.34		Present
Pubali Bank	24.27 (0.00)	2100.05		Present
Rupali Bank	37.74 (0.00)	2084.78		Present

Source: Authors' own calculation using EViews

Note: Numbers in parentheses represent *p*-values

Computed values of the LM test statistic are found to be exceedingly large compared to the 5% critical value. The presence of ARCH effects of share prices is evident. The second column of Table 1 represents the mean share prices of different banks for the entire period. Stock market in Bangladesh, however, experiences frequent fluctuations in terms of individual share price and overall share price indexes. The mean prices therefore are not representative of the actual state of the market. We have introduced five time dummy variables to address the dynamic means of share prices. The dummy variables are able to capture the stylized ups and downs in the share market that occurred before and after January 2017, September 2017, April 2018, March 2019 and January 2020. The corresponding dummy variables are D_{Jan17}, D_{Sep17}, D_{Apr18}, D_{Mar19} and D_{Jan20}. The period after January 2020 is characterized by zero value of all dummies, hence considered as the reference period. We further examine the ARCH effects by estimating the dummy-augmented mean equation and corresponding squared residual as the function of lagged squared residuals described by equations (8) and (9) respectively. Estimates are presented in Table 2. We also present the estimated equations for each bank's share price that helps understand the existence of structural breaks with respect to distinct time points. All of the time dummy variables are found to be soundly significant.

$$y_t = \beta + \rho_1 D_{Jan17} + \rho_2 D_{Sep17} + \rho_3 D_{Apr18} + \rho_4 D_{Mar19} + \rho_5 D_{Jan20} + E_t \quad \ldots \quad (8)$$

$$\hat{E}_t^2 = \vartheta_0 + \vartheta_1 \hat{E}_{t-1}^2 + \Lambda_t \quad \ldots. \quad (9)$$

Estimated equations for

Al Arafah Bank:

$$\underset{(t-statistic)}{\hat{y}_t} = \underset{(73.42)}{15.34} - \underset{(-21.67)}{5.54} D_{Jan17} - \underset{(-13.59)}{3.90} D_{Sep17} + \underset{(16.77)}{3.40} D_{Apr18} + \underset{(17.13)}{2.53} D_{Mar19} + \underset{(12.94)}{3.03} D_{Jan20}$$

Bank Asia:

$$\underset{(t-statistic)}{\hat{y}_t} = \underset{(110.75)}{17.16} - \underset{(-11.27)}{2.14} D_{Jan17} - \underset{(-6.82)}{1.45} D_{Sep17} + \underset{(22.07)}{3.32} D_{Apr18} - \underset{(-7.64)}{0.84} D_{Mar19} + \underset{(6.57)}{1.14} D_{Jan20}$$

BRAC Bank:

$$\underset{(t-statistic)}{\hat{y}_t} = \underset{(41.60)}{40.78} - \underset{(-23.42)}{28.08} D_{Jan17} - \underset{(-9.00)}{12.11} D_{Sep17} + \underset{(21.38)}{20.36} D_{Apr18} + \underset{(19.58)}{13.55} D_{Mar19} + \underset{(18.41)}{20.24} D_{Jan20}$$

IBBL:

$$\underset{(t-statistic)}{\hat{y}_t} = \underset{(53.77)}{18.03} - \underset{(-11.16)}{4.58} D_{Jan17} + \underset{(3.40)}{1.56} D_{Sep17} + \underset{(22.95)}{7.47} D_{Apr18} + \underset{(9.59)}{2.27} D_{Mar19} + \underset{(11.08)}{4.17} D_{Jan20}$$

Pubali Bank:

$$\underset{(t-statistic)}{\hat{y}_t} = \underset{(92.49)}{22.76} - \underset{(-14.87)}{4.47} D_{Jan17} - \underset{(-4.23)}{1.43} D_{Sep17} + \underset{(9.90)}{2.37} D_{Apr18} - \underset{(-3.77)}{0.65} D_{Mar19} + \underset{(9.51)}{2.62} D_{Jan20}$$

Rupali Bank:

$$\underset{(t-statistic)}{\hat{y}_t} = \underset{(36.81)}{28.24} - \underset{(-17.21)}{16.15} D_{Jan17} - \underset{(-11.54)}{12.15} D_{Sep17} + \underset{(23.46)}{17.48} D_{Apr18} + \underset{(10.57)}{5.72} D_{Mar19} + \underset{(7.57)}{6.51} D_{Jan20}$$

Table 2: Estimated Share Price at Different Clusters of Time and Corresponding ARCH Effects

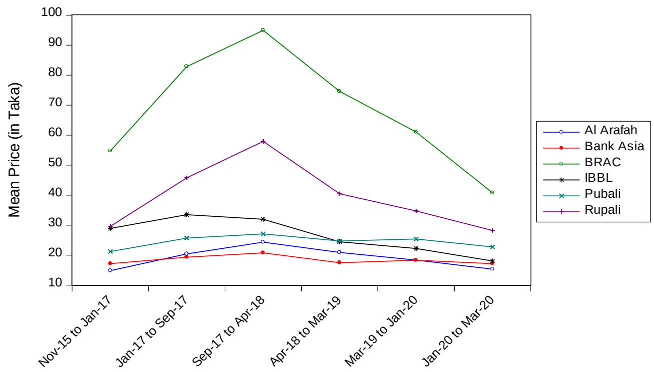
Banks	Estimated Average Share Price						Computed values of LM test statistic $(T\text{-}q)R^2$	ARCH Effects
	Nov 2015 to Jan 2017	Jan 2017 to Sep 2017	Sep 2017 to Apr 2018	Apr 2018 to Mar 2019	Mar 2019 to Jan 2020	Jan 2020 to Mar 2020		
Al Arafah	14.86	20.4	24.3	20.9	18.37	15.34	556.48	present
Bank Asia	17.19	19.33	20.78	17.46	18.30	17.16	518.88	present
BRAC Bank	54.74	82.82	94.93	74.57	61.02	40.78	586.56	present
IBBL	28.92	33.50	31.94	24.47	22.2	18.03	391.04	present
Pubali Bank	21.2	25.67	27.1	24.73	25.38	22.76	451.20	present
Rupali Bank	29.63	45.78	57.93	40.45	34.73	28.23	533.92	present

Source: Authors' own calculation using EViews

Table 2 shows an increase in share price from November 2015 to April 2018 followed by a steep decrease during most of the days in 2018 and 2019. Figure 2 describes the time path of mean share prices of six banks during several clustered periods. Although the fluctuation in the market is due mostly to the manipulators, the recent fall in share price after January 2020 is caused by the adversities of COVID-19 pandemic. Incorporation of time dummies and their statistical significance prove the existence of structural breaks in the time series of share prices.

Examination of structural break is done by considering the period from 2017 to 2020. An attempt to examine the structural breaks for entire sample period will require dozens of time dummies and hence avoided.

Figure 2: Mean Share Price at Different Clusters of Time Horizon



Source: Constructed by the authors using data from the CSE

No exception is observed while considering the ARCH effects even with the dummy-augmented mean equation. For every bank, we notice large values of LM test statistic- evidencing the presence of ARCH effects and time varying volatility or dynamic variance. We then move to estimate the ARCH model for all banks.

Mean equation: $y_t = \psi + e_t$ and variance equation: $B_t = \gamma_0 + \gamma_1 e_{t-1}^2$

Table 3: First Order ARCH Estimates and Dynamic Stability of Variance

Bank	Mean	Variance		Variance Stability
		Constant	ARCH Coefficient	
Al Arafah	14.90***	0.07***	0.99***	stable
Bank Asia	17.86***	0.12***	0.98***	stable
BRAC	34.41***	0.69***	0.99***	stable
IBBL	24.48***	0.16***	1.00***	unstable
Pubali	24.39***	0.21***	0.97***	stable
Rupali	30.17***	0.85***	0.99***	stable

Triple asterisk (***) indicates significant at 1% level.

Estimates of the ARCH model for all banks are significant. Table 3 presents the estimation results. Positivity of variance is also ensured throughout because the estimates of γ_0 and γ_1 are positive. Third and fourth column of Table 3 confirm the positivity of variance. However, variance stability condition $\gamma_1 < 1$ is violated for the share price variance of Islami Bank Bangladesh Ltd (IBBL), which we can see from the fourth column of Table 3. For other cases also, estimates of γ_1 are very close to one, indicating potentially unstable variance. GARCH model might be useful to delve into the dynamic stability of variance.

Estimating the ARCH model, we can forecast the share price ahead and the volatility involved. Volatility is the measure of risk which is a common attribute in share market. Popularity of ARCH model lies in its capacity of making the investors of capital market know the future value of share as well as the degree of uncertainty involved. For example, if the share price in period *t* is y_t and estimated price is $\hat{y}_t$ then $\hat{e}_t = y_t - \hat{y}_t$. Estimated volatility in period (*t+1*) would be $\hat{B}_{t+1} = \hat{\gamma}_0 + \hat{\gamma}_1 \hat{e}_t^2$, computing which the investor decides to invest or refrain from investing.

The above estimation of ARCH model considered only one lag in residual. Therefore, it is ARCH(1) model but more lags might bear significant carryover. Estimation of an ARCH(q) model with q lags in residuals requires the estimation of (q+1) parameters. The corresponding GARCH(1,1) model is able to capture all the features of ARCH(q) model by estimating only three parameters. Table 4 presents the GARCH(1,1) estimates for all sample banks' share price. All the coefficients of estimated GARCH(1,1) model are found significant. Soundly significant GARCH coefficients signify the suitability of GARCH model while investigating the volatility of share prices. Sum of ARCH and GARCH coefficients $(\gamma_1 + \alpha_1)$ being nearly or above one indicates the dynamic instability of variance, which is perhaps the inherent nature of the stock market in Bangladesh. Figure 3, from which divergent nature of volatility is evident, displays how variances of different banks' share prices move over time. In the construction of figure 3, we took subsample of 1,816 latest observations until 4 January 2021 for each bank.

Variance equation: $B_t = \phi + \gamma_1 e_{t-1}^2 + \alpha_1 B_{t-1}$ .... (6)

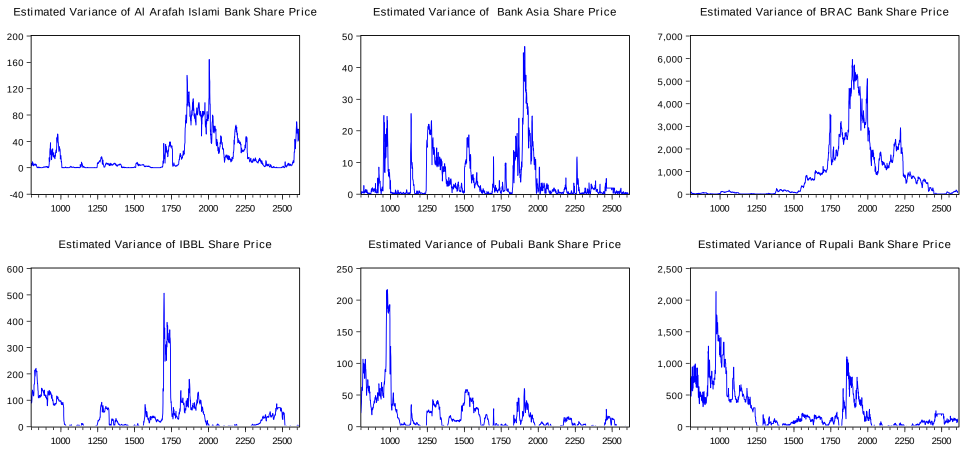
Table 4: GARCH Estimates

Bank	Mean	Variance			Variance Stability
		Constant	ARCH Coefficient	GARCH Coefficient	
Al Arafah	15.0***	0.07***	0.997***	-0.011***	Stable
Bank Asia	17.87***	0.09***	0.841***	0.139***	Stable
BRAC	34.73***	0.32***	0.763***	0.239***	Unstable
IBBL	25.53***	0.08***	0.620***	0.382***	Unstable
Pubali	24.32***	0.05***	0.544***	0.458***	Unstable
Rupali	38.54***	1.20***	0.969***	0.026***	stable

Triple asterisk (***) indicates significant at 1% level

Source: Authors' own calculation

Figure 3: Estimated Dynamic Conditional Variances



Source: Constructed by the Authors using Data from Chittagong Stock Exchange

Finally, we have examined whether positive and negative shocks in the stock market have similar impact on volatility. In general, it is assumed that increase in share price would result in lesser volatility than what would be when share price drops but the estimation output of Threshold-GARCH model does not justify any such evidence. The GARCH model has been extended by including a dummy variable (d_t), which takes zero value when 'good news' in the share market emerges, i.e., share price increases and thereby making $e_t>0$. If share price falls, making $e_t<0$, the value of dummy variable (d_t) would be one. Using 2,155 daily observations till 04 January 2021, we estimated the TGARCH model $B_t = \phi + \gamma_1 e_{t-1}^2 + \delta d_{t-1} e_{t-1}^2 + \alpha_1 B_{t-1}$ for each of the sample banks. Unlike the findings of past studies in the context of other countries, the threshold dummy variable is found insignificant because the null hypothesis $H_0 : \delta = 0$ could not be rejected for any of the six sample banks. Such nonrejection of null hypothesis makes it clearer that the turbulence in the stock market in Bangladesh is equally likely no matter whether the market experiences uptrend or downtrend in share index. Estimates of the coefficient of threshold dummy along with corresponding *p*-values are presented in Table 5.

Table 5: TGARCH Estimates

Bank	Threshold Dummy Coefficient Estimate	*p*-value
Al Arafah	-0.07	0.75
Bank Asia	-0.02	0.87
BRAC	0.01	0.96
IBBL	0.01	0.93
Pubali	0.00	1.00
Rupali	0.04	0.84

Source: TGARCH model $B_t = \phi + \gamma_1 e_{t-1}^2 + \delta d_{t-1} e_{t-1}^2 + \alpha_1 B_{t-1}$ estimated using EViews 10.0

The asymmetric effect of shocks on stock volatility is known as leverage effect. Our present study finds no statistical evidence of leverage effect but the findings of our survey contradicts with Hasan (2017) who found the existence of leverage effect by estimating MA(1)-GARCH(1,1) and MA(1)-EGARCH(1,1) models by using monthly data up to 2012. Latest dataset may be used to estimate the above models and thereby reaching a robust conclusion.

5. Conclusion

Using daily observations of around ten years till 04 January 2021, this paper investigated time varying mean and time varying volatility of stock prices of six selected companies. Time-dummy augmented mean equation and ARCH class models have been used to check time dependent mean and volatility respectively. A representative subsample has been used to show that mean stock prices significantly vary over time. Although volatility in equity market is a common phenomenon all over the world, well developed stock markets rarely experience time-varying mean. Our survey incorporated five time dummy variables in the mean equation corresponding to a subsample of standard size. All of the dummy variables were found soundly significant implying that mean share prices varied over time. Volatility in stock market is a stylized fact no matter how well-developed or under-developed the concerned stock market is, but large swings in mean prices have strong bearing to the portfolio investor as well as policymakers.

Dynamic volatility has been investigated in our paper by testing for ARCH effects. Both time-independent mean equation and time-dummy-augmented mean equation have been estimated to examine ARCH effects. In both cases, significant ARCH effects were observed. Presence of ARCH effects justifies the suitability of ARCH class models and thus we estimated ARCH and GARCH models. Estimation output reveals that GARCH(1,1) model is more suitable than ARCH model for assessing time varying volatility of stock prices because the GARCH coefficient is found soundly significant, indicating longer persistence of volatility. One striking feature of GARCH model estimates is the violation of variance stability condition. Sum of ARCH and GARCH coefficient being nearly or above one signifies the unstable nature of dynamic variances. This finding further confirms the existence of explosive volatility.

Finally, the impact of good and bad news in stock market on volatility has been examined. This empirical test has been carried out using entire sample of 2,615 observations for six companies. In each case, we have observed symmetric effect of shocks. That means, good news and bad news in the stock market have equal amount of impact on volatility. The result clearly contradicts with the previous studies since most of the studies performed earlier found an asymmetric effect of shocks on volatility. In general, when the negative news hits a financial market, asset prices tend to enter a turbulent phase and volatility increases, but with positive news volatility tends to be small (Hill et al., 2011). Even though very few studies are available in the context of Bangladesh, one recent survey carried out by Hasan (2017) concluded that shocks in the stock market influence volatility asymmetrically. That means, good news in the stock market invites less turbulence than what bad news does. Absence of such asymmetric effect in our research seems to be robust because the sample size used is fairly large and statistical evidence is quite strong which is observable from table 5, where the estimates of threshold parameter of TGARCH model are presented.

Our current paper assessed stock price volatility but the reasons of volatility remained unexplored. Although James and Karoglou (2009) found a drop in volatility through foreign participation, a counterfactual simulation may be performed to investigate whether same occurs in case of Bangladesh. Daskalakis et al. (2009) investigated the empirical association between stock market volatility and weather. By using a simple theoretical macroeconomic model, Papadamou et al. (2014) observed a negative link between stock prices volatility and central bank transparency. Buyuksalvarci and Abdioglu (2010) have investigated the cause and effect relationship between stock volatility and key macroeconomic variables.

Unlike many other matured markets, stock markets in Bangladesh sometimes behave exceptionally. One such example is the insignificant impact on share prices of a circular published by the Bangladesh Bank where the announcement of absorbing excess liquidity in the banking system was made and stockholders worried about a potential price drop. Ultimately no such drop was recorded. A thorough survey may be carried out to identify the reasons behind the time varying volatility of stock prices. Also, extended research may be undertaken to justify the absence of leverage effect.

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