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Dynamic Interaction between Conditional Stock Market Volatility and Macroeconomic Uncertainty of Bangladesh

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Abstract

Purpose: The aim of this study is to explore the dynamic linkage between conditional stock market volatility and macroeconomic uncertainty of Bangladesh. **Research design, data, and methodology:** This study uses monthly data covering the time period from January 2005 to December 2018. A comprehensive set of macroeconomic variables, namely industrial production index (IP), consumer price index (CPI), broad money supply (M2), 91-day treasury bill rate (TB), treasury bond yield (GB), exchange rate (EX), inflow of foreign remittance (RT) and stock market index of DSEX are used for analysis. Symmetric and asymmetric univariate GARCH family of models and multivariate VAR model, along with block exogeneity and impulse response functions, are implemented on conditional volatility series to discover the possible interactions and causal relations between macroeconomic forces and stock return. **Results:** The analysis of the study exhibits time-varying volatility and volatility persistence in all the variables of interest. Moreover, the asymmetric effect is found significant in the stock return and most of the growth series of macroeconomic fundamentals. Results from the multivariate VAR model indicate that only short-term interest rate significantly influence the stock market volatility, while conditional stock return volatility is significant in explaining the volatility of industrial production, inflation, and treasury bill rate. **Conclusion:** The findings suggest an increasing interdependence between the money market and equity market as well as the macroeconomic fundamentals of Bangladesh.

Keywords : Stock Market Volatility, Macroeconomic Environment and Uncertainty, GARCH Family of Models, Bangladesh

JEL Classification Code : C32, C54, E44, E60, G10

1. Introduction

The Stock market is the barometer for measuring the economic health of a country. It enables the corporations and business firms to raise a huge amount of long-term capital from a large pool of investors. It also facilitates the investment of surplus funds into financial instruments that better match the liquidity preference and risk appetite of the investors (Leigh, 1997; Olweny & Kimani, 2011). Moreover, it helps to mobilize surplus funds to the most productive and profitable business opportunities, thereby, boosting economic growth and development.

Furthermore, participants of the stock market closely monitor macroeconomic announcements and data released by the authority and accordingly revise their trading decisions upon the advent of new information. Thus, if there is any deviation in the market expectation and announcement, such deviation would lead to the fluctuation in the stock price. Because of the strong affiliation between volatility in the stock market and the macroeconomic environment, financial agents such as analysts, experts, regulators, speculators, etc., have paid great attention to this arena for many years. Moreover, stock market volatility

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influences economic growth in both advanced and emerging economies (Oseni & Nwosa, 2011).

Generally, volatility characterizes the behavior of the stock market (Black, 1976). In finance, volatility is a measure of the variability of financial asset prices or returns. Tokmakcioglu and Tas (2014) stated volatility as a symptom of market disruption. So, at the time of market volatility, the capital market is not functioning smoothly and securities are not priced fairly. Consequently, stock market volatility negatively influences the economic environment of a country. Moreover, the volatility of the stock market could give an important signal to the market participants as to where to allocate their financial resources. It is, therefore, necessary to measure the stock market volatility properly as it is vital for risk management and trading decisions (Martens & Dijk, 2007). Furthermore, excessive volatility can erode investor's confidence in the stock market, increase the possibility of bankruptcy of the individual firms, adversely affect the stock market liquidity, affecting the hedging strategy of the portfolio investors, and diminish economic activities and investments (Daly, 2008).

Therefore, a growing interest has emerged in recent years in investigating the dynamic interaction between macroeconomic fundamentals and stock price and their volatilities in Bangladesh. A fresh study is required in our area of interest to contribute to the existing literature in four main ways. First, previous studies have used the standard GARCH model which merely considers the symmetric effect on the conditional volatility. But, existing literature (such as Asteriou & Hall, 2011; Bollerslev, Chou, & Kroner, 1992; Zivot & Wang, 2006, among others) report the asymmetric effect on the conditional volatility. To overcome the weaknesses of the standard GARCH model, the present study uses GARCH classes of models which can better capture both symmetric and asymmetric effect of shocks on conditional volatility. Second, the previous studies have used three macroeconomic forces such as industrial production, inflation, and exchange rate. The recent study uses seven macroeconomic indicators namely industrial production, inflation, money supply, short-term interest rate, long-term interest rate, exchange rate, and foreign remittance. Third, the previous studies have neglected foreign remittance as one of the variables that may influence the stock price volatility. Considering the important role in influencing the economic development of Bangladesh, this study incorporates foreign remittance as one of the macroeconomic variables. Moreover, Bangladesh Bank (BB) constantly monitors this variable to formulate monetary policy. Finally, this study uses a more recent dataset. This is important given that the Bangladesh stock market regularly experiences some technological changes which may enhance the stock market efficiency, thus accelerating its response to macroeconomic events.

The remainder of the study is outlined as follows. The literature review is presented in Section 2. Section 3 describes the relevant data, variables, and methodology used in this study. Empirical results and discussion of the study are presented in Section 4 and finally, Section 5 concludes the study.

2. Literature Review

The extant literature investigated the explanatory power of the macroeconomic forces in determining the stock market volatility is of mixed nature. Roll (1988) reported that about 33.33 percent of monthly variations in individual stock returns can be explained by systematic macroeconomic forces. Cutler, Poterba, and Summers (1989) also documented that only one-fifth to one-third of stock market fluctuation can be illustrated by the macroeconomic information. The empirical results of Schwert (1989) demonstrated weak evidence that macroeconomic uncertainty can predict stock market volatility. Using the Finnish data, Liljeblom and Stenius (1997) reported that between 16.67 percent and 66.67 percent of the aggregate stock market variance was connected to macroeconomic uncertainty. For the U.S., Corradi, Distaso, and Mele (2013) reported that almost three-fourths of the stock market volatility can be elucidated by macroeconomic fundamentals. Fraser and Power (1997) failed to identify any significant influence of macroeconomic information on the stock market volatility in the U.S., the U.K., and some selected Pacific Rim economies. Morelli (2002) also concluded that selected macroeconomic forces cannot explain the U.K. stock market volatility. Zakaria and Shamsuddin (2012) reported an impoverished linkage between selected macroeconomic volatility and stock market variability in Malaysia. The weak relationship might be due to the dominance of institutional investors in the stock markets and presence of information asymmetry problems among investors. On the other hand, Nikmanesh and Nor (2016) documented that 81% and 75% of stock market variability can be elucidated by the macroeconomic uncertainty and trade openness in Malaysia and Indonesia respectively. The empirical findings of Kasman, Vardar, and Tunc (2011) suggested that macroeconomic volatility had a significant negative influence on the conditional bank stock return volatility in Turkey.

The extant studies on the correlation between variations in macroeconomic fundamentals and stock price volatility are very rich in terms of using different econometric techniques and studying different economies. For developed economies, Paye (2012) investigated the forecasting power of some selected macroeconomic and financial indicators in forecasting future stock market volatility of the US. The findings of the study identified that a set of microeconomic predictors can better capture the stock market volatility. Engle, Ghysels, and Sohn (2013) employed the GARCH-MIDAS model and reported that the selected macroeconomic variables contain sufficient information to predict future stock market volatility in the US at both shorter and longer horizons. However, macroeconomic fundamentals could not explain the Japanese stock market volatility (Choo, Lee, & Ung, 2011). Corradi et al. (2013) developed a no-arbitrage model to explore the macroeconomic determinant of stock market volatility and volatility risk-premiums. Findings of the study showed that business cycle factors were the major predictors to explain the level and variability of stock market volatility.

More recently, Awijen, Zaied, Nguyen, and Sensoy (2020) employed an extended SVAR model to explore the responses of macroeconomic volatility to financial uncertainty shocks by using the U.S. data. Finding of the study documented that increased endogenous financial volatility shocks had a greater impact on macroeconomic uncertainty in the U.S. Shang and Zheng (2021) documented that volatility of the macroeconomic fundamentals, particularly the Composite Leading Indicator, help to fit and anticipate the U.S. and Chinese stock market volatility. Moreover, finding of the study found significant leverage effect in both the U.S. and the Chinese stock market.

For the emerging stock market, Chinzara (2011) studied the association between stock market volatility and macroeconomic uncertainty by employing the GARCH family of models and VAR model and reported that systematic risk originating from macroeconomy significantly influences stock market volatility in South Africa. By using a principal component approach Bilson, Brailsforf, and Hooper (2001) reported that macroeconomic factors are significant in their association with emerging stock returns. Like Bilson et al. (2001), Kumari and Mahakud (2015) also found similar results for the Indian stock market. More recently, Cai, Chen, Hong, and Jiang (2017) investigated the predictive abilities of economic forces in forecasting the Chinese stock market volatility by employing the GARCH-MIDAS model and documented that some selected economic fundamentals can better predict the future volatilities of the Chinese stock market.

Some of the empirical studies were also conducted by considering both developed and emerging economies simultaneously. For instance, Davis and Kutan (2003) examined whether macroeconomic activity measured by the real output and inflation had predictive power for stock return volatility in 13 advanced and emerging economies. The results of the study suggested that macroeconomic volatility was not a very strong predictor of stock market volatility. On the other hand, Bui (2015) found the existence of significant asymmetry in the monetary policy effect on the volatility of five selected ASEAN stock markets.

By using the DCC-GARCH family of models and symmetric and asymmetric causality tests, the study of Jain and Biswal (2016) documented that decrease in oil prices and gold prices cause lower value of Indian stock prices and the currency. Kocaarslan, Sari, Gormus, and Soytas (2017) investigated the time-varying conditional correlations between the US and BRIC stock markets. The finding of the study reported that international commodities and financial market uncertainties were the major contributors to the US and BRIC market dynamics.

A limited number of studies are available in the context of Bangladesh evidencing the association between stock return volatility and variations in macroeconomic uncertainty. For example, Imam and Amin (2004) used GARCH (1, 1) model to forecast the capital market volatility of Bangladesh. The findings of the study reported that there was volatility persistence in return series and conditional volatility after the stock market crash of 1996 was mean reverting. Chowdhury, Mollik, and Akhter (2006) employed GARCH (1, 1) model and VAR model to examine the influence of macroeconomic variability and stock market volatility of Bangladesh and found significant unidirectional causal relation running from industrial production volatility to stock market volatility as well as from stock market volatility to inflation volatility. Their findings also suggested a weak linkage between macroeconomic volatility and volatility in the Bangladesh stock market.

Joarder, Ahmed, Haque, and Hasanuzzaman (2014) investigated the informational efficiency of the Bangladesh stock market by considering macroeconomic variables like monetary aggregates (M1 and M2), industrial production, and exchange rate for the period of 1980 to 2008. The findings of the study showed that past values of selected macroeconomic predictors were able to predict the future stock price changes and concluded that the stock market of Bangladesh is informationally inefficient.

3. Data, Variables, and Methodology

3.1. Data and Variables

The present study attempts to investigate the macroeconomic uncertainty and stock market volatility in Bangladesh by using monthly data spanning the time period from January 2005 to December 2018. Monthly closing prices of the DSE general index (DSEX) is used to estimate the stock market return of Bangladesh. Following the existing literature (see, for example, Adjasi, 2009; Chen, Roll, & Ross, 1986; Chinzara, 2011; Erdem, Arslan, & Erdem, 2005; Groenewold & Fraser, 1997; Kumari &

Muhakud, 2015; Morelli, 2002), this study selects a comprehensive set of macroeconomic variables, such as industrial production index (IP), consumer price index (CPI), broad money supply (M2), 91-day treasury bill rate (TB), treasury bond yield (GB), exchange rate (EX) and inflow of foreign remittance (RT). Though foreign remittance is not truly a macroeconomic variable, it is included because of its strong influence on the Bangladesh economy. Moreover, Bangladesh Bank (the central bank of Bangladesh) constantly observes this variable in formulating the monetary policy.

Prior to modeling, DSEX is converted into compounded monthly returns which are measured as follows:

$$SR_{Mt} = \ln(P_t) - \ln(P_{t-1})$$

Where SR_{Mt} represents the stock market return in month t, In indicates the natural logarithm, P_t designates the DSEX at the end of month t, and P_{t-1} indicates the previous month closing value of DSEX.

With respect to all macroeconomic variables, the same logarithmic transformation is employed to measure the growth rates. All the data series except DSEX, M2, and RT are obtained from International Financial Statistics (IFS) of the International Monetary Fund (IMF). Data series of M2 and RT are collected from the different volumes of Monthly Economic Trends, a monthly bulletin published by the Statistic Department of Bangladesh Bank. DSEX is obtained from the official website of the Dhaka Stock Exchange (DSE). Table 1 shows the Transformation of the variables.

Table 1: Transformation of variables

Variable	Transformation
DSEX	$SR_{Mt} = \ln(P_t) - \ln(P_{t-1})$
IP	$GIP_{Mt} = \ln(IP_t) - \ln(IP_{t-1})$
CPI	$GCPI_{Mt} = \ln(CPI_t) - \ln(CPI_{t-1})$
M2	$GM2_{Mt} = \ln(M2_t) - \ln(M2_{t-1})$
TB	$GTB_{Mt} = \ln(TB_t) - \ln(TB_{t-1})$
GB	$GGB_{Mt} = \ln(GB_t) - \ln(GB_{t-1})$
EX	$GEX_{Mt} = \ln(EX_t) - \ln(EX_{t-1})$
RT	$GRT_{Mt} = \ln(RT_t) - \ln(RT_{t-1})$

3.2. Methodology

3.2.1. GARCH Family of Models

Because of some stylized facts such as volatility clustering, fat tails distribution, volatility mean reversion, volatility asymmetric effect and the leverage effect of the financial data (Bollerslev et al., 1992; Bollerslev, Engle, & Nelson, 1994; Brooks, 2008; Poon & Granger, 2003; Tsay, 2005, among others), it is appropriate to apply volatility models in modeling volatility of financial data series.

Symmetrical and asymmetrical GARCH family of models is employed to analyze the stock market volatility and variations in macroeconomic uncertainties in the Bangladesh stock market. GARCH family of models is used because they are the most appropriate to capture the conditional volatility than any other technique as it is assumed that conditional volatility is time-varying rather than constant.

The specification of the conditional mean and variance equation of the standard GARCH model can be stated as follows:

$$R_t = \mu + \sum_{i=1}^{p} \delta_i R_{t-i} + \sum_{j=1}^{q} \phi_j \epsilon_{t-j} + \epsilon_t \qquad (1)$$

Where, $\epsilon_t \backslash \Omega_{t-1} \sim N(0, h_t)$ and

$$h_t = \omega + \alpha \epsilon^2{}_{t-1} + \beta h_{t-1} \qquad (2)$$

Equation (1) is the mean equation of the GARCH model. R_t represents the series of stock return at time t. μ is the mean value of series. ϵ_t denotes the stochastic error term which is conditional on a previous information set, Ω_{t-1} and is assumed to be normally distributed with a zero mean and variance h_t. R_{t-i} denotes lagged daily return whereas, ε_{t-j} represents the lagged error term. δ_i is the autoregressive coefficient, and ϕ_j denotes the moving average coefficient.

Equation (2) represents the conditional variance equation of the model where h_t represents the conditional variance of the stock return. ω denotes the long-run mean volatility. α is the parameter of lagged squared errors (ARCH term) that are generated from the mean equation and β is the parameter of the lagged conditional volatility (GARCH term). The coefficient of the variance equation should be positive i.e., $\omega>0$, $\alpha\geq0$, $\beta\geq0$ to fulfill the non-negativity conditions and $\alpha+\beta<1$to secure the covariance stationarity of the variance equation. The short-run and long-run persistence of shocks are captured by the ARCH term (α) and GARCH term (β), respectively. Large values for α represent that volatility responds strongly to market movement; whereas, the large values of β indicate that innovation to conditional variance will take a long time to die out. Moreover, ($\alpha+\beta$) closer to unity implies high persistence in volatility clustering.

The asymmetric EGARCH model proposed by Nelson (1991) is used to avoid imposing non-negativity restrictions on the GARCH parameters. Like the GARCH model, the EGARCH model also takes a mean equation similar to equation (1) but its variance equation can be rewritten as follows:

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha \left[\left| \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} - E\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) \right| \right] + \gamma \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \qquad (3)$$

Where γ denotes asymmetric coefficient and is also known as the leverage effect parameter. The effect is said to be asymmetric if $\gamma \neq 0$. The existence of the leverage effect is tested by the hypothesis that $\gamma < 0$. When $\gamma < 0$, good news produces less volatility than bad news. The persistence of volatility is measured by $\sum_{i=1}^{p} \beta_i < 1$.

Zakoian (1994) proposed another asymmetric GARCH model which is popularly known as the threshold GARCH (TGARCH) model. This model is able to discover the leverage effect as well as volatility clustering. This model is an extension of the conventional GARCH model that adds a multiplicative dummy variable as stated by the following conditional variance equation but its mean equation is identical to equation (1).

$$h_t = \omega + \alpha\epsilon^2_{t-1} + \beta h_{t-1} + \gamma\epsilon^2_{t-1} d_{t-1} \quad (4)$$

Where $d_{t-1}=1$ if $\varepsilon_{t-1} < 0$ and $d_{t-1}=0$; otherwise, $\omega>0$ and $|\alpha + \beta| < 1$. γ represents the asymmetric coefficient. The existence of the leverage effect is found if $\gamma > 0$. If $\gamma \neq 0$, the volatility is asymmetric, and if $\gamma = 0$, the volatility is symmetric.

3.2.2. Vector Autoregressive (VAR) Model

In this phase, the Vector Autoregressive (VAR) model proposed by Sims (1980) is used to examine the possible interaction between macroeconomic forces and stock prices. Since the VAR model instigates minor restrictions, it can be used as an efficient means of characterizing the linkage among the economic variables. It is a simultaneous equation model having more than one dependent variable and no restriction is imposed on the framework of the system. As such, this model can be gauged as a flexible estimation of a reduced form of a well-specified but unknown model of an actual economic structure. No differentiation between endogenous and exogenous variables is made in this model whenever simultaneity is found among a number of variables (Sims, 1980). All the variables in the systems will be treated as endogenous if this differentiation is discarded. Therefore, in the reduced form of the VAR model, every equation has the same set of regressors. This study has employed the multivariate VAR model inspired by those of Abugri (2008), Kumari and Mahakud (2015) which are expressed as follows:

$$\mathrm{hDSEX}_t = \Pi_0 + \sum_{i=1}^{p} \vartheta\, \mathrm{hDSEX}_{t-i} + \sum_{i=1}^{p} \rho\, \mathrm{hmv}_{jt-i} + \varepsilon_t \quad (5)$$

$$\mathrm{hmv}_t = \Gamma_0 + \sum_{i=1}^{p} \text{Ⓠ}\, \mathrm{hmv}_{jt-i} + \sum_{i=1}^{p} \partial\ \mathrm{hDSEX}_{t-i} + \varepsilon_t \quad (6)$$

Where $hDSEX_t$ indicates the conditional stock price (return) volatility at time t. hmv_t denotes the conditional variance of macroeconomic fundamental j at time t and i represents the lag length. The parameters of lagged values of the conditional stock price (returns) volatility are denoted by ϑ and ∂, whereas, ρ and Ⓠ designate the coefficient of lagged values of the conditional variance of macroeconomic variable j. This ascertains whether conditional stock price (return) volatility is linked to the conditional variance of macroeconomic fundamentals and vice versa.

Even though the VAR structure is suitable to investigate the relationship among and between economic variables, it is not free from shortcoming. It makes the estimated model difficult to interpret when a large number of coefficients involved in the system. Particularly the signs of parameters of several lag variables may change across the lags which make it complex to observe how a given change in a variable would affect the future values of the variable in the system. To overcome this limitation, the VAR model is estimated by using a set of statistics, such as block exogeneity, and impulse response functions.

3.2.2.1. Block Exogeneity Test

The block exogeneity test aims to segregate the economic variables that have a significant influence on each of the dependent variables from those of the variables that do not. To accomplish this objective, it restricts all the coefficients of a particular lag variable to zero under the VAR system. Therefore, the present study employs the block exogeneity test to determine which of the macroeconomic variables significantly influence the stock price volatility and vice versa.

3.2.2.2. Impulse Response Function (IRF)

IRF traces out the sensitiveness of a dependent variable to innovations to each of the other variables in the VAR system. In every individual equation, a one-unit shock is imposed on the residual of each variable in that equation and the responses are observed in the VAR structure. In this study, IRF uncovers the response of stock return volatility to one-unit shock in any of the macroeconomic volatility. The analysis of this study captures the sign, magnitude, and persistence of responses of one market to innovations and shocks in another market. Since the Cholesky decomposition method does not require orthogonalization of shocks and does not vary with the ordering of the variables, this study also uses this method for the ordering of the variables.

4. Empirical Results and Discussion

4.1. Descriptive Analysis

Table 2 represents the descriptive statistics of the time series data for the stock returns and the growth rate of macroeconomic fundamentals. Stock returns show a substantial fluctuation between the maximum and minimum values. Moreover, monthly mean values of stock returns are positive implying that the DSEX series increased over time.

For macroeconomic variables, there is no consistency of increase in growth series. For instance, the money supply has grown fastest followed by industrial production, remittance, and consumer price index but Treasury bill and government bond yield grew negatively. The skewness measure shows that some of the growth series are negatively skewed while some others are positively skewed. All of the variables of interest exhibit evidence of excess kurtosis suggesting that the series are fat-tailed or leptokurtic. The normality of the data series is rejected based on the Jarque-Bera test statistics suggesting that all the series except for the flow of remittance are non-normal. To check the autocorrelation in the series, LB test is applied which suggests the existence of significant autocorrelation in all of the series except for the treasury bill rate. The existence of significant autocorrelation indicates the presence of volatility clustering in the selected variables.

4.2. ARCH-LM Test

Table 3 exhibits the outcomes of ARCH-LM test which demonstrates that the return series and all the macroeconomic variables are significant implying the evidence of ARCH effect in the series. Therefore, it is justified to use GARCH type of models to model the conditional volatility.

4.3. Correlation Analysis

Table 4 exhibits the correlation matrix. Consistent with existing literature and empirical studies the signs of the correlation coefficient between stock return and different macroeconomic variables are as anticipated except for industrial production and consumer price index. Moreover, the matrix provides evidence of insignificant correlations (in most cases) between stock return and selected macroeconomic variables.

Table 2: Descriptive Statistics of all variables

	DSEX	IP	CPI	M2	TB	GB	EX	RT
Mean	0.007	0.010	0.005	0.014	-0.003	-0.002	0.002	0.009
Median	0.009	0.015	0.005	0.013	0.000	0.000	0.000	0.002
Maximum	0.264	0.201	0.043	0.049	0.958	0.187	0.047	0.462
Minimum	-0.351	-0.267	-0.014	-0.021	-1.141	-0.217	-0.026	-0.377
SD	0.078	0.079	0.009	0.011	0.163	0.049	0.009	0.136
Skewness	-0.693	-0.715	0.223	0.237	-0.508	-0.447	2.759	-0.056
Kurtosis	7.185	4.497	3.883	3.895	27.951	11.293	15.361	3.678
Jarque-Bera	118.643	27.391	9.743	10.019	3515.81	519.335	1079.11	3.975
Prob.	0.000	0.000	0.048	0.037	0.000	0.000	0.000	0.197
LB(10)	29.915	66.435	73.255	29.355	15.711	27.794	31.525	67.341
Prob.	0.000	0.000	0.000	0.002	0.275	0.017	0.021	0.000

Table 3: ARCH-LM test results

Variable	DSEX	IP	CPI	M2	TB	GB	EX	RT
F-statistic	8.195**	5.974**	4.085***	9.205*	3.156***	5.126**	3.346***	4.941**
P values	0.015	0.042	0.061	0.000	0.068	0.029	0.082	0.025

Note: *, ** & *** indicates that the test statistics are significant at 0.01, 0.05 and 0.10 levels, respectively.

Table 4: Correlation Matrix

	DSEX	IP	CPI	M2	TB	GB	EX	RT
DSEX	1.000							
IP	-0.009	1.000						
CPI	-0.077	-0.295**	1.000					
M2	0.291*	0.317*	0.006	1.000				
TB	-0.083	-0.071	0.135	-0.027	1.000			
GB	-0.119	0.023	-0.081	0.123	0.257*	1.000		
EX	-0.149***	0.121	-0.079	-0.052	0.176***	0.085	1.000	
RT	0.011	0.576*	-0.058	0.332*	-0.052	0.115	0.2886*	1.000

Note: *, ** & *** indicates that the t-test statistic is significant at 0.01, 0.05 and 0.10 levels, respectively.

4.4. Stationarity Test

This study applies Augmented Dickey-Fuller (1981) (ADF) and Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS) and Phillips-Perron (1988) (PP) stationarity test to verify the stationarity of the growth series. ADF and PP tests hypothesized the presence of unit root; whereas, null of stationary in the series were examined by the KPSS test. The results documented in Table 5 indicate that stock return and selected macroeconomic variables are stationary at level. Therefore, all the variables of interest are of I(0) type of series.

4.5. Results and Discussion of GARCH Family of Models

The results of the GARCH family of models are reported in Table 6.

Since residuals of all of the variables were serially correlated, we added autoregressive term(s) in the mean equation and found that most of the series became sufficiently uncorrelated (i. e., became white noise) after incorporating one autoregressive component (i. e., AR (1)).

The results reported in Table 6 of Panel A showed that the symmetric GARCH model appropriately captured the volatility persistence in the return series and growth series of all of the macroeconomic variables as all the parameters are different from zero. The parameter α (ARCH term) of CPI and RT and the parameter β (GARCH term) of RT were found insignificant but for all other variables, these two parameters were statistically significant, implying that past price values of the respective variables and past values of conditional variance are better able to capture the future volatility.

Table 5: Unit root tests

Variables	Augmented Dickey Fuller (ADF) Test Statistic		Phillips-Perron(PP) Test Statistic		Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test Statistic	
	Constant	Constant & Trend	Constant	Constant & Trend	Constant	Constant & Trend
DSEX	-12.792*	-12.778*	-12.792*	-12.778*	0.143	0.094
IP	-5.175*	-5.133*	-46.605*	-46.594*	0.113	0.099
CPI	-2.967**	-3.411***	-6.927*	-6.774*	0.151	0.075
M2	-4.059*	-4.738*	-17.371*	-17.378*	0.331	0.115
TB	-11.942*	-11.751*	-11.919*	-11.921*	0.109	0.061
GB	-4.927*	-4.967*	-13.901*	-13.989*	0.327	0.106
EX	-8.174*	-8.222*	-9.462*	-9.504*	0.207	0.088
RT	-14.762*	-8.751*	-28.661*	-38.862*	0.291	0.112
Critical values of test statistic						
At 1%	-3.477	-4.024	-3.477	-4.024	0.739	0.216
At 5%	-2.881	-3.442	-2.882	-3.442	0.463	0.146
At 10%	-2.578	-3.145	-2.578	-3.145	0.347	0.119

Note: Lag length for ADF test statistic was determined by using AIC; whereas, the bandwidths for both PP and KPSS test statistic were selected by considering Newey-West automatic suggestion following Bartlett Kernel estimation. *, ** & *** designate acceptance of alternative hypothesis at 0.01, 0.05 and 0.10 levels, respectively.

Table 6: Estimates of GARCH family of models

	DSEX	IP	CPI	M2	TB	GB	EX	RT
Panel A: GARCH model								
ω	0.001***	0.000**	8.04E-06	6.53E-05**	0.010	0.000*	1.44E-06*	0.005
α	0.195**	-0.055**	-0.003	0.107*	-0.024*	0.297*	1.468*	0.149
β	0.631*	1.032*	0.889*	0.549**	0.701*	0.572*	0.379*	0.413
α + β	0.826	0.977	0.886	0.656	0.677	0.869	1.847	0.562
LL	167.225	195.853	482.941	446.397	61.346	267.191	569.866	125.373
AIC	-2.271	-2.547	-6.717	-6.189	-0.779	-3.637	-7.972	-1.667
SIC	-2.167	-2.443	-6.613	-6.085	-0.675	-3.532	-7.868	-1.563
Diagnostic tests								
LB (10)	5.279	86.773*	23.642*	12.023	10.931	13.011	4.476	34.352*
$LB^2(10)$	2.411	9.894	1.803	18.069***	5.719	1.047	2.720	11.294
ARCH	0.116	0.668	0.203	0.057	0.023	0.000	0.142	0.138

Panel B: EGARCH Model								
ω	-7.792*	-6.380*	-18.623*	-5.392*	-3.942*	-8.385*	-2.565*	-2.024
α	0.142	-0.255	0.034	-0.733*	-0.227	0.864*	0.248*	0.216
β	-0.473*	-0.208	-0.921*	0.349***	-0.093	-0.220**	0.833*	0.596
γ	-0.280*	-0.491*	-0.198*	0.230	0.166	-0.410*	0.207*	0.005
α + β	-0.331	-0.463	-0.887	-0.384	-0.320	0.644	1.081	0.812
LL	168.176	185.229	482.716	448.582	56.414	260.695	567.730	122.469
AIC	-2.284	-2.524	-6.714	-6.234	-0.710	-3.587	-7.912	-1.640
SIC	-2.159	-2.399	-6.589	-6.109	-0.585	-3.462	-7.787	-1.516
Diagnostic tests								
LB (10)	7.2449	92.731*	30.510*	10.135	10.520	20.321	8.9046	33.858*
$LB^2(10)$	1.5826	4.8258	2.6501	11.774	4.7567	2.9327	6.5495	11.332
ARCH	0.002	0.0199	0.192	0.706	0.055	0.008	0.188	0.668
Panel C: TGARCH model								
ω	0.002**	0.001	2.91E-05	6.04E-05**	0.010	0.000*	1.30E-06*	0.005
α	-0.001	0.142	-0.055	-0.102*	0.020	0.016	0.288*	0.164
β	0.539*	0.802*	0.619	0.606**	0.731*	0.504*	0.584*	0.388
γ	0.374*	-0.209	0.017	-0.015	-0.046	0.572**	.635*	-0.038
α + β	0.538	0.945	0.564	0.504	0.741	0.521	0.872	0.552
LL	168.784	183.362	481.971	443.019	52.502	267.975	576.174	123.394
AIC	-2.293	-2.498	-6.704	-6.155	-0.655	-3.690	-8.031	-1.639
SIC	-2.168	-2.373	-6.579	-6.030	-0.530	-3.565	-7.906	-1.494
Diagnostic tests								
LB (10)	6.335	84.741*	25.274*	13.131	11.578	16.852	4.991	34.158*
$LB^2(10)$	1.725	6.989	2.594	17.690***	4.926	1.235	3.461	11.016
ARCH	0.007	0.428	0.001	0.190	0.199	0.085	0.304	0.157

Note: *, ** and *** represent the significance at 1%, 5% and 10%, respectively. ω stands for the constant value of Variance equation. α, β and γ represent the ARCH term, GARCH term, and leverage term, respectively. α + β indicate the stationary condition of the GARCH model. LL represents the Log-likelihood. LB(10) and $LB^2(10)$ indicate the Ljung-Box statistics for standardized residuals and squared standardized residuals using 10 lags, respectively. ARCH represents the ARCH-LM test for heteroscedasticity. AIC and SIC represent Akaike information Criteria and Schwarz information criteria, respectively.

The outputs of the asymmetric EGARCH model were documented in Panel B of Table 6. The results showed that the asymmetric coefficient was significant for the growth series of DSEX, IP, CPI, GB, and EX. This indicated that negative (positive) innovation has a higher influence on conditional variance than those of the positive (negative) innovation of equal magnitude. This kind of phenomenon in the financial time series data was reported in several empirical literatures (for example, Adjasi, 2009; Chinzara, 2011; Erdem et al., 2005; Kumari & Mahakud, 2015, among others). For those series that exhibited significant asymmetry, the standard GARCH model was not adequate and suitable to analyze volatility. Thus, a further evaluation was carried out between the EGARCH and TGARCH models. The result of the TGARCH model was documented in Panel C of Table 6, which revealed that news impact is as asymmetric as $\gamma \neq 0$. The sign of γ was found to be negative in some growth series, while it was positive in some other growth series. This indicated that both positive and negative shocks simultaneously influence the stock market volatility, suggesting the presence of leverage effect.

It is noted here that the leverage effect parameter was significant for DSEX, GB, and EX. Comparing the results of EGARCH and TGARCH models, the latter model (TGARCH model) was found to be appropriate for GB and EX, since, it satisfied the stationarity condition, significant value of leverage parameters and had a minimum AIC and SIC value, whereas, the former model was more appropriate for DSEX, IP and CPI. However, the asymmetric effect was not evident in the remaining macroeconomic variables. Therefore, the standard GARCH model was appropriate for them. The best fit models for stock return and macroeconomic variables were reported in Table 7. The standardized residuals from the best fit models were scrutinized for serial autocorrelation and heteroscedasticity to ensure the appropriateness and robustness of the selected models. To check for any remaining serial autocorrelation, Ljung-Box (LB) test was performed. Results of the two statistics of LB test, i.e., LB (10) and LB^2 (10), showed that they were insignificant at the traditional significance level. So, there was no evidence of serial autocorrelation and heteroscedasticity in the models. Moreover, the ARCH-LM test could not detect any ARCH effect in the residuals. Therefore, it can be concluded that the selected models are well specified.

Table 7: The best-fit model

Variable	Best fit model
DSEX	AR (1)-EGARCH (1,1)
IP	AR (1)-EGARCH (1,1)
CPI	AR (1)-EGARCH (1,1)
M2	AR (1)-GARCH (1,1)
TB	AR (1)-GARCH (1,1)
GB	AR (1)-TGARCH (1,1)
EX	AR (1)-TGARCH (1,1)
RT	AR (1)-GARCH (1,1)

4.6. Results and Discussion of Vector Auto Regression (VAR) Model

Table 8 reported the results of the multivariate VAR model. Panel A of Table 8 demonstrated that only the treasury bill is statistically significant at the 1% level. This finding signifies that conditional volatility of short-term interest rate (i.e., Treasury bill) influences the conditional stock return volatility. However, results of the other macroeconomic forces such as, industrial production, consumer price, money supply, long-term interest rate, exchange rate, and foreign remittance are not statistically significant to affect the conditional volatility of stock returns. So, the volatility of these macroeconomic fundamentals has minimum influence on stock return volatility. Further, multivariate VAR model is used to examine whether stock return volatility has any impact on macroeconomic volatility, which is reported in panel B of Table 8. The results showed that industrial production, consumer price index, and Treasury bill rate are statistically significant at the traditional significance level, meaning that conditional stock return volatility is significant in explaining the volatility of industrial production, inflation, and Treasury bill rate. It suggests that stock return volatility directly transmits to macroeconomic volatility. Moreover, Consistent with the empirical findings of Abugri (2008), Chinzara (2011), Kumari and Mahakud (2015), this study finds a bidirectional causal relationship between stock price and short-term interest rate but a unidirectional causal relationship running from stock price to industrial production and inflation.

4.6.1. Impulse Response Analysis

Ten-month IRFs are estimated by using the Cholesky decomposition method to investigate the speed, sign, and persistence of volatility and response of stock price volatility to one-unit innovation (shock) in volatilities of each of the macroeconomic fundamentals and vice versa. An innovation to a particular variable (say *i*th variable) not only directly influences that variable but is also transmitted to other endogenous variables through the dynamic VAR structure. An impulse response function sketches the impact of one standard error innovation to one of the shocks on the present and future values of the endogenous variables. The graphs of impulse response functions are depicted in figure 1. Impulse responses are shown by the thick lines in the middle; whereas, the dotted lines represent standard error bands. The response of stock return volatility to macroeconomic volatility and vice versa is evaluated simultaneously through the plotted figures.

Responses of stock return volatility to one standard deviation shock in the volatility of macroeconomic fundamentals are persistent and diverse. The left column of Figure 1 demonstrates the response of stock market volatility to macroeconomic shock. It is found that responses to industrial production, consumer price index, money supply, and government bond yield are insignificant. But the response to the Treasury bill rate and the exchange rate is positive. These results are expected as an increase in the volatility of these macroeconomic forces will also increase the stock return volatility. Stock return is very much sensitive to one standard deviation shock to the remittance. It signifies that the Bangladesh stock market is also influenced by the foreign flow of remittance. Therefore, innovations in the macroeconomic volatility lead to magnify the effect of both systematic and unsystematic risk and, thus, influence the stock return volatility. As a result, investors in the stock market should keep a close eye on the changes in the macroeconomic environment and accordingly rebalance their portfolios. These results are consistent with the findings reported in Abugri (2008), Chinzara (2011), Corradi et al. (2013), Kumari and Mahakud (2015).

The results regarding the response of macroeconomic volatility to one-unit shock in the stock returns volatility is also found diverse. If one-unit shock is given to the stock returns then an immediate positive response to the industrial production, consumer price index, Treasury bill rate, exchange rate, and foreign remittance is detected but the duration and magnitude of their responses are different. For instance, the industrial production volatility responds positively in the first three and a half months but responds negatively thereafter. The consumer price index exhibits high volatility over the entire horizon. The responses to the money supply and long-term interest rate are found insignificant whereas volatility of exchange rate and remittance is significant and positive over the entire horizon.

Table 8: F-statistics from Multivariate VAR model

	VIP	VCPI	VM2	VTB	VGB	VEX	VRT
Panel A: Predictive power of stock return volatility							
	0.532	0.555	0.624	5.510*	1.071	1.391	1.208
Panel B: Predictive power of Macroeconomic volatility							
	2.975*	2.278**	0.557	2.969*	0.504	0.931	0.668

Note: *, ** & *** indicate that the test statistics are significant at 0.01, 0.05 and 0.10 levels, respectively. VIP, VCPI, VM2, VTB, VGB, VEX, and VRT represent the variance series of industrial production, consumer price index, money supply, treasury bill, government bond, exchange rate, and foreign remittance, respectively, which were derived from the best-fit GARCH family of models.

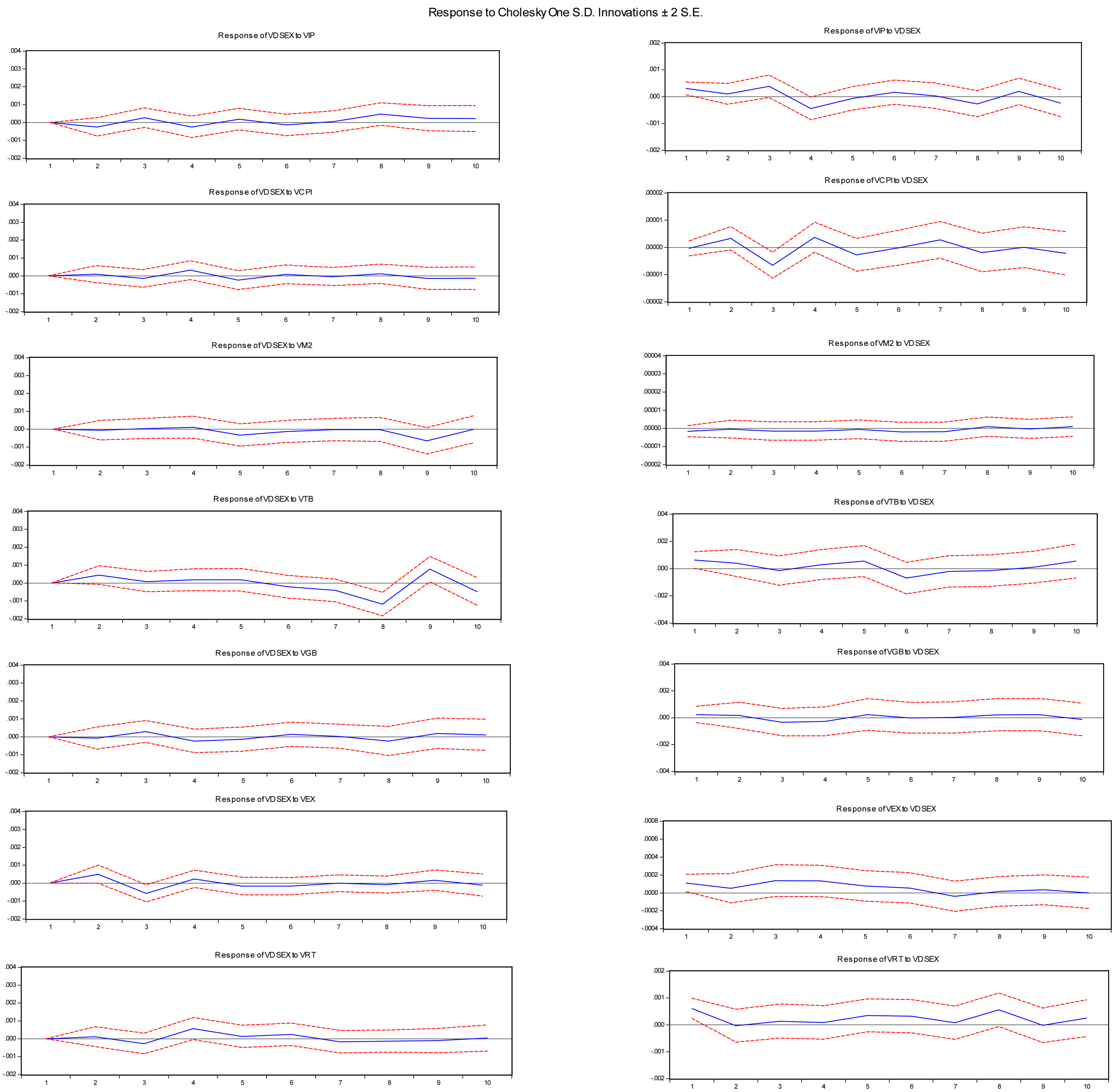

Figure 1: Impulse Response Analysis

Table 9: Block Exogeneity Test Statistics

	VIP	VCPI	VM2	VTB	VGB	VEX	VRT
Panel A: Predictive power of stock return volatility							
	5.316	5.552	6.244	55.095*	10.706	13.911	12.081
Panel B: Predictive power of Macroeconomic volatility							
	29.7480*	22.775*	5.572	29.690*	5.041	9.312	6.678

Note: *, ** & *** indicate that the test statistics are significant at 0.01, 0.05, and 0.10, levels, respectively. VIP, VCPI, VM2, VTB, VGB, VEX, a nd VRT represent the variance series of industrial production, consumer price index, money supply, treasury bill, government bond, ex change rate and foreign remittance, respectively and were derived from the best-fit GARCH family of models.

4.6.2. Block Exogeneity Test

This study uses the block exogeneity test to explore the role of each of the macroeconomic variables in explaining the volatility of stock returns. The test statistic of the block exogeneity test is reported in Table 9.

Panel A of Table 9 reveals that only the Treasury bill can predict the stock market volatility; whereas, Table 9 of panel B reports that stock market volatility can significantly influence the volatility of industrial production, consumer price index, and treasury bill. These results suggest the existence of a bidirectional causal relationship between the volatility of stock returns and the treasury bill rate; and also the presence of a unidirectional causality from stock return volatility to industrial production and inflation volatility. These results are analogous to the findings of those of Chinzara (2011) and Morelli (2002) who pointed that majority of the macroeconomic variables could not affect the volatility of the stock market. The findings of the block exogeneity test are consistent with the results of impulse response functions which are discussed earlier in this section.

5. Conclusion

This study empirically investigated the influence of macroeconomic uncertainty on the volatility of the stock market by using monthly data ranging from January 2005 to December 2018. This study employed two-step estimation procedures. First, symmetric and asymmetric univariate GARCH family of models were used to capture the time-varying conditional volatilities from economic variables. Second, a multivariate VAR model along with block exogeneity and impulse response functions was implemented on conditional volatility series to examine the possible interactions and causal relations between macroeconomic forces and stock returns.

Time-varying volatility and volatility persistence were evident from the estimates of the GARCH family of models. The asymmetric effect was found significant in the DSEX series and most of the growth series of macroeconomic fundamentals. This indicated that negative innovation had a higher impact on conditional volatility than those of the positive innovation of equal magnitude.

Results from the multivariate VAR model indicated that only short-term interest rate (i.e., TB) significantly influenced the stock market volatility, while conditional stock return volatility was significant in explaining the volatility of industrial production, inflation, and treasury bill rate. In other words, the findings confirmed the ability of some of the volatility of macroeconomic fundamentals in explaining the stock market volatility. It was also observed from the findings that there was a bidirectional causal relationship between stock market volatility and changes in treasury bill rate and a unidirectional relationship leading from stock return volatility to industrial production and inflation volatility. This relation can be interpreted as an increasing interdependence between the money market and equity market as well as macroeconomic fundamentals in Bangladesh.

The findings of the study have certain implications for the stock market participants, policymakers, and regulators. Investors of Bangladesh stock markets should keep eyes on the short-term interest rate, industrial production index, exchange rate, and foreign flow of remittance as dominant sources of systematic risk in making the investment and formulating portfolio diversification strategies. Stock market regulators and policymakers should also take into account these macroeconomic factors in formulating and implementing policies relating to the stock market and overall economic stability.

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