

Modelling Co-movement of Different Sectors in Dhaka Stock Exchange (DSE) Using Asymmetric BVAR-GARCH Models

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Abstract This paper tries to investigate the financial shock transmission dynamics using daily return data under different sectors traded in Dhaka Stock Exchange (DSE). Bayesian VAR model was used as conditional mean in GJR-GARCH, scalar-diagonal VECH and BEKK GARCH models to test return and volatility spillover effects. Lagged squared residuals and lagged conditional variances were used as variance regressors in conditional variance of GJR-GARCH to test the spillover effects. Finding reveals a highly significant memory effect on all sector returns except one. Asymmetric versions of GARCH, VECH and BEKK identified significant effect of news about volatility, past memory and differential effect of bad news on conditional volatility of almost all series. GJR-GARCH results identified pharmaceutical sector spillover free yet all other pairs were found to be unidirectional or in some cases bidirectional. Co-volatility among almost all sectors is also observed from VECH and BEKK output.

Keywords: *volatility spillover, return spillover, Bayesian VAR, GJR-GARCH, VECH, BEKK, DSE*

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1. Introduction

An organized and well developed capital market is crucial for acceleration of economic growth. The adoption of international quality trading and settlement mechanisms, removal of barriers for international equity investors, reduced transaction costs have made investors more optimistic which resulted in a considerable growth in market volume and liquidity. Investors always prefer to see stability in the economy and scope for efficient diversification in a market they would like to invest. Dhaka Stock Exchange (DSE) experienced restructuring of policies after it had experienced major crashes particularly in the year 1996 and 2011 where an abnormal rise in price was observed. This happened due to syndicated trading and a sharp decrease in price resulted soon after investors lost trust in the market and realized that it has violated the norms of fundamental asset pricing and reached to an abnormally high level.

Generally, investors invest their capital with an expectation to make a gain from it over time and volatility can only make it happen. Although, volatility is attributed as risk, it is a very vital ingredient for a healthy stock market and it should always be there to induce speculators important to maintain liquidity in the market. However, volatility graph of a healthy stock market should not have any abnormal rise or fall. With rapid advancement in media communication technology, financial shocks originated in one industry or market can easily be

transmitted to other industry in the same market or outside the market and can be reflected in the volatility of price and return. To design effective portfolio allocation and hedging decisions, it is crucial to analyze shock transmission dynamics between stock market participants.

Stock market serves as an important indicator of economic condition and the volatility analysis among stock indices available in an economy is crucial to understand a country's economic health. It is therefore vital to analyze the performance of stock markets and its volatility since asset pricing model states that the return of an asset depends on its own return variance or to the covariance between its return and the return on the market portfolio (e.g. [33]).

International investors are now looking for emerging economies, less integrated with global economy, to diversify capital due to increased integration among developed economies. Several empirical studies have been performed on volatility spillover or financial shock transmission across commodities and markets of developed economies. However, a dearth of research findings is there on volatility transmission dynamics of emerging economies like Bangladesh. It has been observed that Bangladesh stock market is less integrated among other emerging and developed economies as it has experienced sustained growth in GDP even when rest of the world experienced recession in recent past. This poor integration attracted vast interest of global investors as it provides enormous diversification benefits. Nonetheless, Bangladesh stock market is still in weak condition with no empirical studies to examine the volatility and return

spillover across industries in the same market to provide scope for diversification for international investors. The main objective of this study is to investigate co-movement dynamics as return and volatility spillover among major sectors (engineering, food, pharmaceuticals, fuel & power, and commercial banking sectors) traded in DSE so that international investors can efficiently diversify their capital to cultivate maximum return with minimum risk.

This paper is segmented into six sections. The first section contains the introductory part of the paper while the second section of the study presents an overview of related literatures. The third section covers the primary data description and summary statistics whereas the fourth section provides information on empirical models. The fifth section presents all empirical results and findings. Finally, sixth section of the paper presents the conclusion of the study with possible recommendation.

2. Literature Review

Modelling volatility in financial time series has been the object of much attention ever since the introduction of the Autoregressive Conditional Heteroskedasticity (ARCH) model. A large body of this literature has been devoted to the univariate models; see [7] and [13]. While the economic integration of industries within a market or across international markets becomes obvious, the relations between the volatilities and co-volatilities of different stock indices or markets have become the centre of attention.

DSE could provide huge opportunities of effective diversification to global investors as it was the least integrated with developed economies among all other emerging economies. Diversification benefit increases with the decrease in correlation and co-movement between industries in a market and between markets. International investors planning to invest in Bangladesh should have clear information on co-movement dynamics between different sectors so that they can create a minimum variance portfolio by diversifying capital among least correlated sectors. Rigorous research on financial integration through return and volatility spillover between stock market sectors of DSE can only provide knowledge on required co-movement dynamics. The author could find only a handful number of researches on modelling volatility of DSE but failed to identify research on return and volatility spillover across industries of Bangladesh stock market.

Reference [3] and [31] observed Generalized Autoregressive Conditional Heteroskedasticity (GARCH) properties in the daily and monthly DSE returns where [2,3] and [14] used different GARCH framework to identify best model to forecast volatility. Different lag orders of ARCH and GARCH was used by [26] on four listed companies of DSE where GARCH (1,1) is found to be the best volatility model. Reference [34] also used different ARCH and GARCH orders to model volatility of daily returns of DSE general index (DGEN) from January, 2002 to July, 2013 and observed reasonable market volatility from 2002 to 2009. The market exhibited abnormal volatility from 2010 to 2011 and declined drastically after the collapse of 2011. Reference [27] used

auto-correlation structure and GARCH framework in the returns of DGEN and DSE 20 index but could not find any asymmetric or differential impact of bad and good news on the conditional variance of DSE returns. However, they observed significant effect of historical volatility on DSE returns in the form of highly significant autocorrelation. Reference [26] used different GARCH specifications and observed significant ARCH presence in DSE stock returns. Based on the findings GARCH (1,1) is found to be the best model. Reference [5] observed a significant negative relationship between conditional volatility and stock returns and attributed circuit breaker as a causal factor that contributed to the volatility of realized returns. Reference [30] examined a wide variety of GARCH models under different distributional assumption but models under Student-t distributional assumptions are found to be suitable for modelling volatility of Chittagong Stock Exchange (CSE). Reference [15] compared stock market volatility of CSE and DSE using closing price of four companies such as Aftab Automobiles, Bata Shoe Company, Beximco Pharmaceutical and Southeast Bank and DGEN from May, 2000 to April, 2014 using GARCH models where CSE is found more volatile. Reference [16] also used different GARCH specification and identified GARCH (1, 3) as the best forecasting model based on Akaike Information Criteria (AIC) and Schwartz Information Criteria (SIC).

Research on volatility spillovers has stirred huge interest amongst investigators and practitioners to develop models that can accurately forecast volatility. Despite this enthusiasm, establishing which models are superior in forecasting volatility is crucial. There has been a lot of theoretical research on measuring volatility based on models of the GARCH/ ARCH family, and their respective extensions. By allowing the current variance to depend on its previous lags the model is able to include all the necessary information into a much simpler and more parsimonious equation than is often the case with ARCH. GARCH provides a reliable volatility measure since both the market trend and its corresponding volatility pattern are simultaneously accounted for over time (e.g. [12]).

GARCH models enforce symmetric response to positive and negative volatility shocks. This occurs due to the squaring of the lagged residuals in the conditional variance equation, and therefore losing the signs (e.g. [9]). Since, there is a general consensus that a negative shock is likely to increase the level of volatility more than a positive shock of the same magnitude, a symmetric GARCH may not account for potential leverage effects (e.g. [9]). This limitation has led to the development of further extensions of the GARCH model. An extension of univariate GARCH model that address potential asymmetries is referred to as GJR-GARCH developed by [13]. Empirical results vary on which of these models provides the best volatility forecasts. According to the research done by [25] GJR-GARCH achieves the most accurate volatility forecasts with EGARCH just slightly behind. Asymmetric GARCH model attracted extensive research on the volatility transmission in the context of the Asian financial crisis and the 2007-9 subprime mortgage crisis (see [17], [6], and [28] among others). Reference [25] mentioned that when asymmetries are ignored GARCH model with normality assumption is preferable to the

usual error distribution models. Modelling asymmetric components is vital than specifying error distribution to improve volatility forecasts of financial returns with heavy tails, leptokurtic and skewed leverage effects.

Numerous researches on volatility spillover have been carried out using multivariate GARCH models like VECH-GARCH developed by [8], BEKK-GARCH developed by [4]. Reference [19] used BEKK framework and observed volatility spillover among almost all Asian stock markets. Reference [29] detected significant volatility spillover across all Gulf stock markets using BEKK GARCH. Reference [20] used VAR-BEKK GARCH and observed higher integration of Chinese stock market after global financial crisis of 2008. Among other researchers like [1] and [32] also used VAR BEKK GARCH for volatility spillover analysis.

This paper utilized Bayesian version of Vector Autoregressive (BVAR) model in the conditional mean equation of asymmetric VECH GARCH, BEKK GARCH and GJR-GARCH model to predict return and volatility spillover among engineering, food, pharmaceuticals, fuel & power, and commercial banking sectors of DSE.

3. Data Description and Summary Statistics

To analyze the diffusion of volatility or volatility spillover effects between different sectors traded in DSE, we have collected daily price data from January, 2009 to January, 2016 of forty seven companies consisting of five sectors, five from each of engineering (A), food (B), and power & fuel sectors (D), four from pharmaceuticals (C) and the rest from commercial banking sectors (E). Index price for these sectors has been calculated by taking the un-weighted daily average and then converted into continuously compounded rate of return (R_t) after taking the first difference of the log prices that is, $R_t = \ln(P_t / P_{t-1})$.

Table 1 provides descriptive statistics analysis on daily returns of DSE. The normality test has been carried out by estimating skewness, kurtosis and Jarque-Bera coefficient of all returns. Except food industry, all returns exhibit loss with a very small mean. The frequency of negative returns of commercial banks for the period of 2009 to 2016 was

found to be higher compared to other sectors. The standard deviations of returns are much greater than the means in absolute value, indicating that the means are not significantly different from zero. This is clearly an indication that financial time series at this frequency follows a random walk. Engineering sector exhibits the highest volatility (5.43%), followed by commercial banks (4.512%) and food industry (4.501%). The distribution of all returns are negatively skewed and leptokurtic which indicates that the distributions are asymmetric, and that the probability of observing large negative returns is higher than that of a normal distribution. The Jarque-Bera test statistics (e.g. [18]) confirms the rejection of the null hypothesis of normality for all returns. The Ljung-Box Q-statistic at 12 and 24 lags are obtained for returns to test whether the series are white noise or if there is any autocorrelation up to that order. Here, we fail to reject the null hypothesis that there is no autocorrelation up to 12 and 24 lags except for banking series at 12 lag.

The correlation of market returns exhibited in Table 2 can be inferred as a gauge of the co-movement between sectors. A higher value of correlation indicates a higher level of co-movement between industries which implies that it is more difficult to diversify portfolio risk by investing in different sectors. Table 2 also reveals that all returns are positively related that means all the stocks have been moving in the same direction (up or down). The highest co-movement is found between engineering and food sectors while lowest is observed between pharmaceuticals and power sectors.

In Table 3, Pairwise Granger causality test reveals highly significant bi-directional causality between commercial banks and all other individual sectors. No trend over time was observed in the returns under study although variables in a regression with trend over time results in higher coefficient of multiple determination even when the variables are unrelated. To test the stationarity, Augmented Dickey Fuller (ADF) and Phillips-Perron test of unit roots was used in Table 4 to make sure that the outcome of the analysis is not spurious (e.g. [10] and [11]). Figure 1 and Figure 2 depicts the returns exhibit volatility clustering as periods of low volatility mingle with periods of high volatility. This clearly indicates presence of ARCH effect in the series.

Table 1. Descriptive Statistics of Daily Returns of DSE

	Engineering	Food Ind.	Pharma Ind	Power & Fuel	Bank
Mean	-0.001227	0.000172	-0.000287	-0.001290	-0.002094
Median	-0.000936	0.000429	-0.000622	-0.001067	-0.001436
Maximum	0.238211	0.103615	0.101869	0.129299	0.128381
Minimum	-1.948576	-1.673586	-1.142988	-0.875007	-1.678044
Std. Dev.	0.054292	0.045015	0.033378	0.030652	0.045119
Skewness	-27.56900	-30.28521	-23.86018	-14.63628	-30.19412
Kurtosis	978.0200	1125.336	810.7501	396.8881	1120.889
Observations	1701	1701	1701	1701	1701
LB-Q(12)	17.502	12.164	7.2902	11.697	20.637*
LB-Q(24)	17.502	21.090	16.202	17.543	22.718
Jarque-Bera	67593788***	89536870***	46404512***	11056837***	88829220***

*** at 1% level of significance.

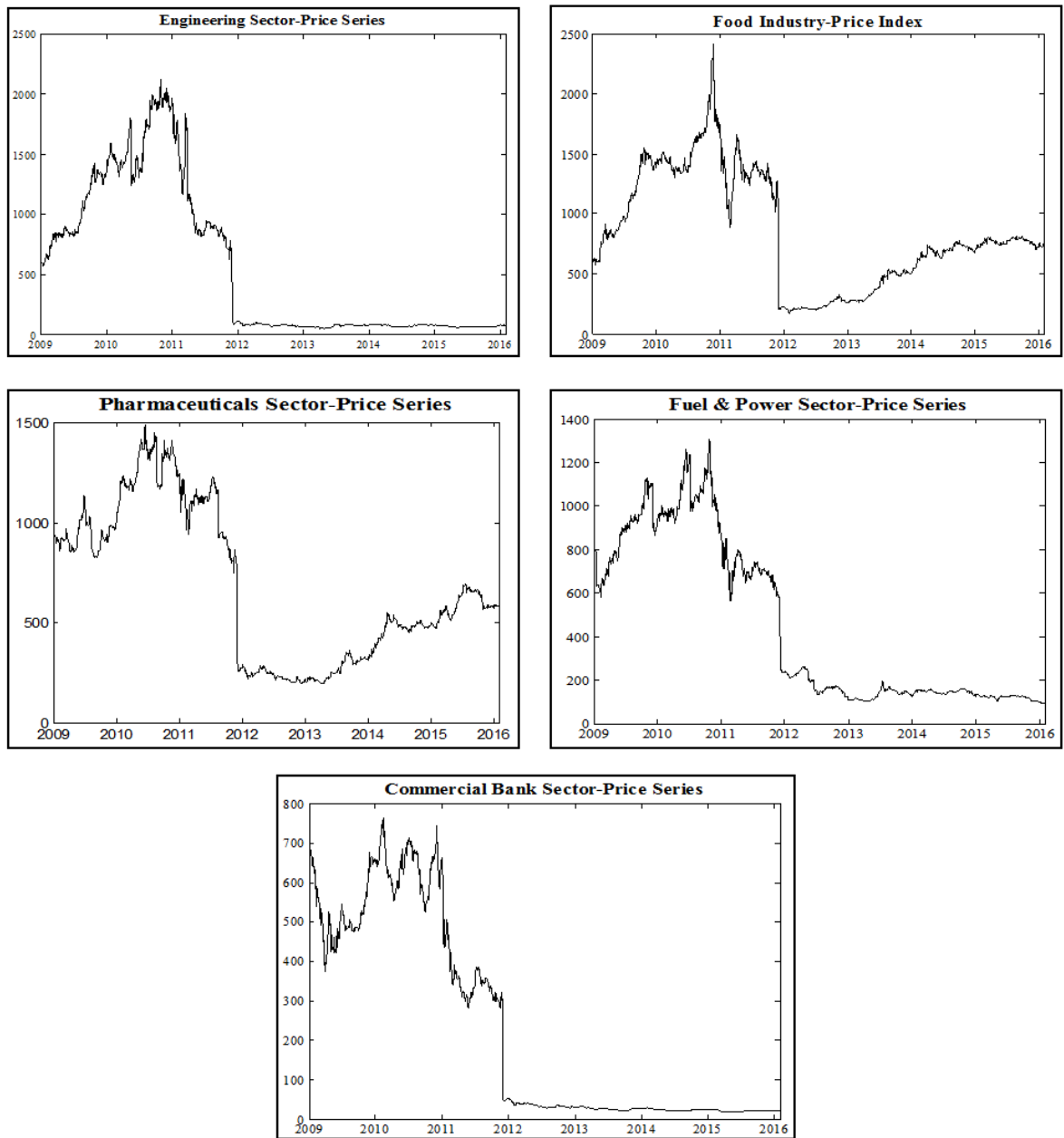


Figure 1. Daily price series

Table 2. Correlation Matrix of different Sectors

	Engineering(A)	Food Ind.(B)	Pharma Ind.(C)	Power & Fuel(D)
Engineering (A)				
Food Ind. (B)	0.8747			
Pharma Ind (C)	0.8156	0.8545		
Power & Fuel (D)	0.7283	0.7502	0.6986	
Banks (E)	0.8442	0.8729	0.8262	0.7102

Table 3. Results of Pairwise Granger Causality Tests of different Sectors

Regressors	Response Variables				
	Engineering(A)	Food Ind.(B)	Pharma Ind.(C)	Power & Fuel(D)	Banks (E)
Engineering (A)		0.72724	2.6E-05	0.13039	18.8324***
Food Ind. (B)	0.33765		1.11554	0.93472	21.9752***
Pharma Ind (C)	1.29725	0.78498		0.33298	12.2464***
Power & Fuel (D)	0.44211	0.04263	0.04092		8.86324***
Banks (E)	32.5039***	40.3160***	23.7295***	10.4676***	

*** at 1% level of significance.

Table 4. Results of Unit Root Test of different Sectors

Variables	ADF Test	Phillips-Perron Test
Engineering (A)	-40.44770***	-40.49429***
Food Ind. (B)	-40.16005***	-40.21433***
Pharma Ind (C)	-40.74438***	-40.74885***
Power & Fuel (D)	-39.89357***	-39.88240***
Bank (E)	-26.38923***	-39.96805***

*** at 1% level of significance.

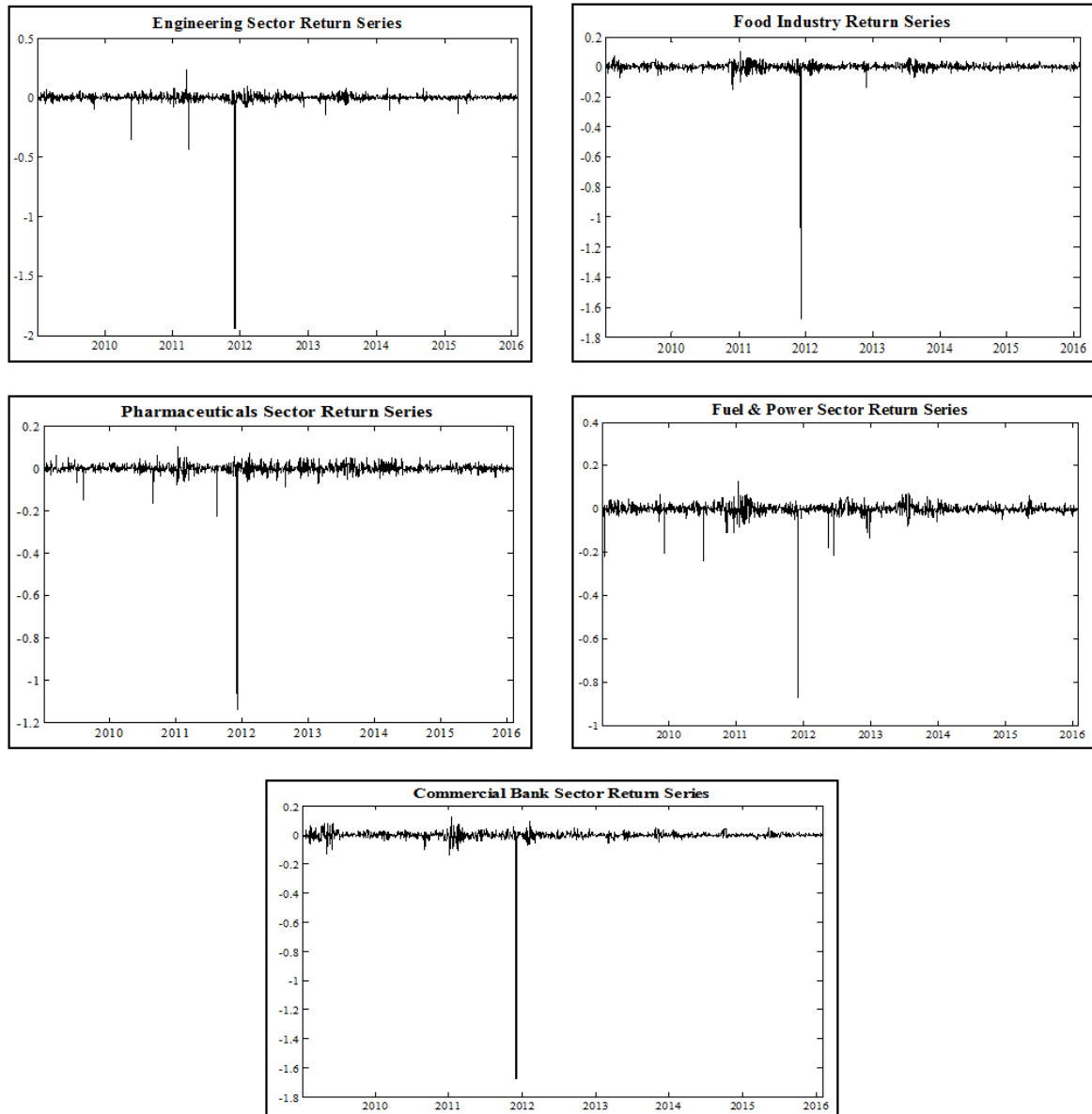


Figure 2. Daily return series

4. Empirical Models

This paper utilized Bayesian version of vector autoregression (BVAR) to test return spillover among engineering, food, pharmaceuticals, fuel & power, and commercial banking sectors of DSE. Furthermore, the paper also used VAR equations as conditional mean equation in GARCH models to test volatility spillover between these returns. Endogenous variables are considered up to two lags in the VAR based on SIC. The vector autoregressions is used for analysing dynamic impact of random innovations on a system of interrelated

times series. The difference of BVAR with traditional VAR is that the model parameters are treated as random variables, and prior probabilities are assigned to them.

The parameter space of VARs proliferates with the number of dependent variables and the number of lags and this over-parameterization problem is resolved by Bayesian shrinkage through restrictions on parameter set (e.g. [21]). In this paper we have used Minnesota prior (proposed by [23] and [24] and subsequently developed by other researchers at University of Minnesota,) to assign prior probabilities to random model parameter. BVAR equations 1 through 5 was used later as conditional mean equations of GARCH models.

$$A = \theta_A + \sum_{i=1}^2 \omega_i A_{t-i} + \sum_{j=1}^2 \delta_j B_{t-j} + \sum_{k=1}^2 \psi_k C_{t-k} \quad (1)$$

$$+ \sum_{l=1}^2 \eta_l D_{t-l} + \sum_{m=1}^2 \kappa_m E_{t-m} + \varepsilon_{A_t}$$

$$B = \theta_B + \sum_{i=1}^2 \omega_i B_{t-i} + \sum_{j=1}^2 \delta_j C_{t-j} + \sum_{k=1}^2 \psi_k D_{t-k} \quad (2)$$

$$+ \sum_{l=1}^2 \eta_l E_{t-l} + \sum_{m=1}^2 \kappa_m A_{t-m} + \varepsilon_{B_t}$$

$$C = \theta_C + \sum_{i=1}^2 \omega_i C_{t-i} + \sum_{j=1}^2 \delta_j D_{t-j} + \sum_{k=1}^2 \psi_k E_{t-k} \quad (3)$$

$$+ \sum_{l=1}^2 \eta_l A_{t-l} + \sum_{m=1}^2 \kappa_m B_{t-m} + \varepsilon_{C_t}$$

$$D = \theta_D + \sum_{i=1}^2 \omega_i D_{t-i} + \sum_{j=1}^2 \delta_j E_{t-j} + \sum_{k=1}^2 \psi_k A_{t-k} \quad (4)$$

$$+ \sum_{l=1}^2 \eta_l B_{t-l} + \sum_{m=1}^2 \kappa_m C_{t-m} + \varepsilon_{D_t}$$

$$E = \theta_E + \sum_{i=1}^2 \omega_i E_{t-i} + \sum_{j=1}^2 \delta_j A_{t-j} + \sum_{k=1}^2 \psi_k B_{t-k} \quad (5)$$

$$+ \sum_{l=1}^2 \eta_l C_{t-l} + \sum_{m=1}^2 \kappa_m D_{t-m} + \varepsilon_{E_t}$$

In the BVAR model five endogenous variables of returns have been used up to two lags in a system of equation where A, B, C, D and E represents engineering, food, pharmaceuticals, power & fuel, and banking sectors, respectively. The ω coefficients indicate impact of historical return or memory effects while δ , ψ , η , and κ specify spillover effect on endogenous variables. The $\varepsilon_t = [\varepsilon_{A_t}, \varepsilon_{B_t}, \varepsilon_{C_t}, \varepsilon_{D_t}, \varepsilon_{E_t}]'$ is a vector of residuals that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right hand side variables and the residuals are assumed to be normally distributed with mean zero and covariance H_t or σ_t^2 .

On the other hand, in the Threshold GARCH or GJR-GARCH model impact of historical volatility is measured by β and short run persistence of shocks to returns is identified by α where long run persistence is measured by $\alpha + \beta$. A dummy variable (d_{t-1}) was used in the model to capture the differential impact of good news and bad news on volatility where, $d_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $d_{t-1} = 0$ otherwise. If the estimated value of $\gamma > 0$ then the asymmetry effect or leverage effect is present and bad news ($\varepsilon_{t-1} < 0$) or negative shocks increases volatility more than the good news ($\varepsilon_{t-1} > 0$). In this model, we have used historical volatility (conditional variance) and historical news about volatility (squared residual) up to two lags to test spillover effect on one series from all other series. We have used maximum likelihood estimation (MLE) method in Threshold GARCH model assuming that errors are

normally distributed. MLE method involves in estimating the unknown parameters in such a manner that the probability of observing the endogenous is as high as possible. Estimated parameter values are no different in MLE than OLS except that the estimated conditional variance is biased downward in small samples but in asymptotically large sample this bias tends to be zero i.e. the estimated value of conditional variances converges to its true value. Residual diagnostic test like Ljung-Box Q-statistics has been performed to check for any serial correlation in the conditional mean equation and correlogram of squared residuals and ARCH LM test has been performed to check for any remaining ARCH in the variance equation. The conditional variance equations from 6 to 10 in GJR-GARCH model is expressed as:

$$\sigma_{A_t}^2 = \eta_A + \alpha \varepsilon_{A_{t-1}}^2 + \beta \sigma_{A_{t-1}}^2 + \gamma \varepsilon_{A_{t-1}}^2 d_{t-1} + \sum_{i=1}^2 \xi_{B_i} \sigma_{B_{t-i}}^2 + \sum_{i=1}^2 \varphi_{B_i} \varepsilon_{B_{t-i}}^2 + \sum_{i=1}^2 \xi_{C_i} \sigma_{C_{t-i}}^2 + \sum_{i=1}^2 \varphi_{C_i} \varepsilon_{C_{t-i}}^2 \quad (6)$$

$$+ \sum_{i=1}^2 \xi_{D_i} \sigma_{D_{t-i}}^2 + \sum_{i=1}^2 \varphi_{D_i} \varepsilon_{D_{t-i}}^2 + \sum_{i=1}^2 \xi_{E_i} \sigma_{E_{t-i}}^2 + \sum_{i=1}^2 \varphi_{E_i} \varepsilon_{E_{t-i}}^2$$

← Spillover Regressors →

$$\sigma_{B_t}^2 = \eta_B + \alpha \varepsilon_{B_{t-1}}^2 + \beta \sigma_{B_{t-1}}^2 + \gamma \varepsilon_{B_{t-1}}^2 d_{t-1} + \sum_{i=1}^2 \xi_{A_i} \sigma_{A_{t-i}}^2 + \sum_{i=1}^2 \varphi_{A_i} \varepsilon_{A_{t-i}}^2 + \sum_{i=1}^2 \xi_{C_i} \sigma_{C_{t-i}}^2 + \sum_{i=1}^2 \varphi_{C_i} \varepsilon_{C_{t-i}}^2 \quad (7)$$

$$+ \sum_{i=1}^2 \xi_{D_i} \sigma_{D_{t-i}}^2 + \sum_{i=1}^2 \varphi_{D_i} \varepsilon_{D_{t-i}}^2 + \sum_{i=1}^2 \xi_{E_i} \sigma_{E_{t-i}}^2 + \sum_{i=1}^2 \varphi_{E_i} \varepsilon_{E_{t-i}}^2$$

← Spillover Regressors →

$$\sigma_{C_t}^2 = \eta_C + \alpha \varepsilon_{C_{t-1}}^2 + \beta \sigma_{C_{t-1}}^2 + \gamma \varepsilon_{C_{t-1}}^2 d_{t-1} + \sum_{i=1}^2 \xi_{A_i} \sigma_{A_{t-i}}^2 + \sum_{i=1}^2 \varphi_{A_i} \varepsilon_{A_{t-i}}^2 + \sum_{i=1}^2 \xi_{B_i} \sigma_{B_{t-i}}^2 + \sum_{i=1}^2 \varphi_{B_i} \varepsilon_{B_{t-i}}^2 \quad (8)$$

$$+ \sum_{i=1}^2 \xi_{D_i} \sigma_{D_{t-i}}^2 + \sum_{i=1}^2 \varphi_{D_i} \varepsilon_{D_{t-i}}^2 + \sum_{i=1}^2 \xi_{E_i} \sigma_{E_{t-i}}^2 + \sum_{i=1}^2 \varphi_{E_i} \varepsilon_{E_{t-i}}^2$$

← Spillover Regressors →

$$\sigma_{D_t}^2 = \eta_D + \alpha \varepsilon_{D_{t-1}}^2 + \beta \sigma_{D_{t-1}}^2 + \gamma \varepsilon_{D_{t-1}}^2 d_{t-1} + \sum_{i=1}^2 \xi_{A_i} \sigma_{A_{t-i}}^2 + \sum_{i=1}^2 \varphi_{A_i} \varepsilon_{A_{t-i}}^2 + \sum_{i=1}^2 \xi_{B_i} \sigma_{B_{t-i}}^2 + \sum_{i=1}^2 \varphi_{B_i} \varepsilon_{B_{t-i}}^2 \quad (9)$$

$$+ \sum_{i=1}^2 \xi_{C_i} \sigma_{C_{t-i}}^2 + \sum_{i=1}^2 \varphi_{C_i} \varepsilon_{C_{t-i}}^2 + \sum_{i=1}^2 \xi_{E_i} \sigma_{E_{t-i}}^2 + \sum_{i=1}^2 \varphi_{E_i} \varepsilon_{E_{t-i}}^2$$

← Spillover Regressors →

$$\sigma_{E_t}^2 = \eta_E + \alpha \varepsilon_{E_{t-1}}^2 + \beta \sigma_{E_{t-1}}^2 + \gamma \varepsilon_{E_{t-1}}^2 d_{t-1} + \sum_{i=1}^2 \xi_{B_i} \sigma_{B_{t-i}}^2 + \sum_{i=1}^2 \varphi_{B_i} \varepsilon_{B_{t-i}}^2 + \sum_{i=1}^2 \xi_{C_i} \sigma_{C_{t-i}}^2 + \sum_{i=1}^2 \varphi_{C_i} \varepsilon_{C_{t-i}}^2 \quad (10)$$

$$+ \sum_{i=1}^2 \xi_{D_i} \sigma_{D_{t-i}}^2 + \sum_{i=1}^2 \varphi_{D_i} \varepsilon_{D_{t-i}}^2 + \sum_{i=1}^2 \xi_{A_i} \sigma_{A_{t-i}}^2 + \sum_{i=1}^2 \varphi_{A_i} \varepsilon_{A_{t-i}}^2$$

← Spillover Regressors →

Furthermore, we have used an asymmetric representation of the multivariate VECG GARCH developed by [8] using MLE method assuming errors are normally distributed where the parameters are restricted to rank N Cholesky factorized or full ranked matrix to ensure that the conditional variance is positive definite matrix and the operator “ \bullet ” is the element by element product of matrices. The expression of the model is expressed using matrix notation in equation (11). Here, $[h_t]$ is the conditional variance-covariance matrix, χ is the scalar matrix for constant, α , β and γ are $[N(N+1)/2 \times N(N+1)/2]$ or $[15 \times 15]$ diagonal matrices of coefficients for ARCH, GARCH and TARCH terms respectively. If the estimated value of TARCH or $\gamma > 0$ then the asymmetry effect or leverage effect is present and bad news ($\varepsilon_{t-1} < 0$) or negative shocks increases volatility more than the good news ($\varepsilon_{t-1} > 0$). A dummy

variable (d_{t-1}) was also used in the model to capture the differential impact of good news and bad news on volatility where, $d_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $d_{t-1} = 0$ otherwise. Where $[M]$ represents individual diagonal matrices of coefficients of ARCH, GARCH and TARCH and for ARCH, $M = \alpha$, for GARCH, $M = \beta$ and for TARCH, $M = \gamma$.

This paper also used asymmetric version of the multivariate diagonal scalar BEKK GARCH initially developed by [4] and extended with asymmetric property by [22]. In scalar diagonal BEKK specification of equation (12), $[h_t]$ is the conditional variance-covariance matrix, χ is scalar matrix for constant, α , β and γ are the (5×5) diagonal matrices of coefficients for ARCH, GARCH and threshold ARCH or TARCH terms respectively and the operator “ \bullet ” is the element by element product of matrices.

Scalar Diagonal-VECH Specification:

$$[h_t] = \chi + \alpha \bullet ARCH + \beta \bullet [h_{t-1}] + \gamma \bullet TARCH \tag{11}$$

$$\begin{aligned}
 [h_t] = & \begin{bmatrix} \sigma_{A,t}^2 \\ \sigma_{AB,t} \\ \sigma_{AC,t} \\ \sigma_{AD,t} \\ \sigma_{AE,t} \\ \sigma_{B,t}^2 \\ \sigma_{BC,t} \\ \sigma_{BD,t} \\ \sigma_{BE,t} \\ \sigma_{C,t}^2 \\ \sigma_{CD,t} \\ \sigma_{CE,t} \\ \sigma_{D,t}^2 \\ \sigma_{DE,t} \\ \sigma_{E,t}^2 \end{bmatrix}, [h_{t-1}] = \begin{bmatrix} \sigma_{A,t-1}^2 \\ \sigma_{AB,t-1} \\ \sigma_{AC,t-1} \\ \sigma_{AD,t-1} \\ \sigma_{AE,t-1} \\ \sigma_{B,t-1}^2 \\ \sigma_{BC,t-1} \\ \sigma_{BD,t-1} \\ \sigma_{BE,t-1} \\ \sigma_{C,t-1}^2 \\ \sigma_{CD,t-1} \\ \sigma_{CE,t-1} \\ \sigma_{D,t-1}^2 \\ \sigma_{DE,t-1} \\ \sigma_{E,t-1}^2 \end{bmatrix}, ARCH = \begin{bmatrix} \varepsilon_{A,t-1}^2 \\ \varepsilon_{A,t-1}\varepsilon_{B,t-1} \\ \varepsilon_{A,t-1}\varepsilon_{C,t-1} \\ \varepsilon_{A,t-1}\varepsilon_{D,t-1} \\ \varepsilon_{A,t-1}\varepsilon_{E,t-1} \\ \varepsilon_{B,t-1}^2 \\ \varepsilon_{B,t-1}\varepsilon_{C,t-1} \\ \varepsilon_{B,t-1}\varepsilon_{D,t-1} \\ \varepsilon_{B,t-1}\varepsilon_{E,t-1} \\ \varepsilon_{C,t-1}^2 \\ \varepsilon_{C,t-1}\varepsilon_{D,t-1} \\ \varepsilon_{C,t-1}\varepsilon_{E,t-1} \\ \varepsilon_{D,t-1}^2 \\ \varepsilon_{D,t-1}\varepsilon_{E,t-1} \\ \varepsilon_{E,t-1}^2 \end{bmatrix}, TARCH = \begin{bmatrix} \varepsilon_{A,t-1}^2(d_{A,t-1}) \\ \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{B,t-1}(d_{B,t-1}) \\ \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{C,t-1}(d_{C,t-1}) \\ \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{D,t-1}(d_{D,t-1}) \\ \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) \\ \varepsilon_{B,t-1}^2(d_{B,t-1}) \\ \varepsilon_{B,t-1}(d_{B,t-1})\varepsilon_{C,t-1}(d_{C,t-1}) \\ \varepsilon_{B,t-1}(d_{B,t-1})\varepsilon_{D,t-1}(d_{D,t-1}) \\ \varepsilon_{B,t-1}(d_{B,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) \\ \varepsilon_{C,t-1}^2(d_{C,t-1}) \\ \varepsilon_{C,t-1}(d_{C,t-1})\varepsilon_{D,t-1}(d_{D,t-1}) \\ \varepsilon_{C,t-1}(d_{C,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) \\ \varepsilon_{D,t-1}^2(d_{D,t-1}) \\ \varepsilon_{D,t-1}(d_{D,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) \\ \varepsilon_{E,t-1}^2(d_{E,t-1}) \end{bmatrix} \\
 [M] = & \begin{bmatrix} M_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & M_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & M_{13} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & M_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & M_{15} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & M_{22} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & M_{23} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_{24} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_{25} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_{33} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_{34} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_{35} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_{44} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_{45} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & M_{55} \end{bmatrix}
 \end{aligned}$$

Scalar Diagonal-BEKK Specification:

$$[h_t] = \chi + \alpha \bullet [ARCH] \bullet \alpha' + \beta \bullet [h_{t-1}] \bullet \beta' + \gamma \bullet [TARCH] \bullet \gamma' \quad (12)$$

$$\alpha = \begin{bmatrix} \alpha_{11} & 0 & 0 & 0 & 0 \\ 0 & \alpha_{22} & 0 & 0 & 0 \\ 0 & 0 & \alpha_{33} & 0 & 0 \\ 0 & 0 & 0 & \alpha_{44} & 0 \\ 0 & 0 & 0 & 0 & \alpha_{55} \end{bmatrix}, \quad \beta = \begin{bmatrix} \beta_{11} & 0 & 0 & 0 & 0 \\ 0 & \beta_{22} & 0 & 0 & 0 \\ 0 & 0 & \beta_{33} & 0 & 0 \\ 0 & 0 & 0 & \beta_{44} & 0 \\ 0 & 0 & 0 & 0 & \beta_{55} \end{bmatrix}, \quad \gamma = \begin{bmatrix} \gamma_{11} & 0 & 0 & 0 & 0 \\ 0 & \gamma_{22} & 0 & 0 & 0 \\ 0 & 0 & \gamma_{33} & 0 & 0 \\ 0 & 0 & 0 & \gamma_{44} & 0 \\ 0 & 0 & 0 & 0 & \gamma_{55} \end{bmatrix}$$

$$[h_t] = \begin{bmatrix} \sigma_{A,t}^2 & \sigma_{AB,t} & \sigma_{AC,t} & \sigma_{AD,t} & \sigma_{AE,t} \\ \sigma_{AB,t} & \sigma_{B,t}^2 & \sigma_{BC,t} & \sigma_{BD,t} & \sigma_{BE,t} \\ \sigma_{AC,t} & \sigma_{BC,t} & \sigma_{C,t}^2 & \sigma_{CD,t} & \sigma_{CE,t} \\ \sigma_{AD,t} & \sigma_{BD,t} & \sigma_{CD,t} & \sigma_{D,t}^2 & \sigma_{DE,t} \\ \sigma_{AE,t} & \sigma_{BE,t} & \sigma_{CE,t} & \sigma_{DE,t} & \sigma_{E,t}^2 \end{bmatrix}, \quad [h_{t-1}] = \begin{bmatrix} \sigma_{A,t-1}^2 & \sigma_{AB,t-1} & \sigma_{AC,t-1} & \sigma_{AD,t-1} & \sigma_{AE,t-1} \\ \sigma_{AB,t-1} & \sigma_{B,t-1}^2 & \sigma_{BC,t-1} & \sigma_{BD,t-1} & \sigma_{BE,t-1} \\ \sigma_{AC,t-1} & \sigma_{BC,t-1} & \sigma_{C,t-1}^2 & \sigma_{CD,t-1} & \sigma_{CE,t-1} \\ \sigma_{AD,t-1} & \sigma_{BD,t-1} & \sigma_{CD,t-1} & \sigma_{D,t-1}^2 & \sigma_{DE,t-1} \\ \sigma_{AE,t-1} & \sigma_{BE,t-1} & \sigma_{CE,t-1} & \sigma_{DE,t-1} & \sigma_{E,t-1}^2 \end{bmatrix}$$

$$ARCH = \begin{bmatrix} \varepsilon_{A,t-1}^2 & \varepsilon_{A,t-1}\varepsilon_{B,t-1} & \varepsilon_{A,t-1}\varepsilon_{C,t-1} & \varepsilon_{A,t-1}\varepsilon_{D,t-1} & \varepsilon_{A,t-1}\varepsilon_{E,t-1} \\ \varepsilon_{A,t-1}\varepsilon_{B,t-1} & \varepsilon_{B,t-1}^2 & \varepsilon_{B,t-1}\varepsilon_{C,t-1} & \varepsilon_{B,t-1}\varepsilon_{D,t-1} & \varepsilon_{B,t-1}\varepsilon_{E,t-1} \\ \varepsilon_{A,t-1}\varepsilon_{C,t-1} & \varepsilon_{B,t-1}\varepsilon_{C,t-1} & \varepsilon_{C,t-1}^2 & \varepsilon_{C,t-1}\varepsilon_{D,t-1} & \varepsilon_{C,t-1}\varepsilon_{E,t-1} \\ \varepsilon_{A,t-1}\varepsilon_{D,t-1} & \varepsilon_{B,t-1}\varepsilon_{D,t-1} & \varepsilon_{C,t-1}\varepsilon_{D,t-1} & \varepsilon_{D,t-1}^2 & \varepsilon_{D,t-1}\varepsilon_{E,t-1} \\ \varepsilon_{A,t-1}\varepsilon_{E,t-1} & \varepsilon_{B,t-1}\varepsilon_{E,t-1} & \varepsilon_{C,t-1}\varepsilon_{E,t-1} & \varepsilon_{D,t-1}\varepsilon_{E,t-1} & \varepsilon_{E,t-1}^2 \end{bmatrix}$$

$$TARCH = \begin{bmatrix} \varepsilon_{A,t-1}^2(d_{A,t-1}) & \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{B,t-1}(d_{B,t-1}) & \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{C,t-1}(d_{C,t-1}) & \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{D,t-1}(d_{D,t-1}) & \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) \\ \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{B,t-1}(d_{B,t-1}) & \varepsilon_{B,t-1}^2(d_{B,t-1}) & \varepsilon_{B,t-1}(d_{B,t-1})\varepsilon_{C,t-1}(d_{C,t-1}) & \varepsilon_{B,t-1}(d_{B,t-1})\varepsilon_{D,t-1}(d_{D,t-1}) & \varepsilon_{B,t-1}(d_{B,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) \\ \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{C,t-1}(d_{C,t-1}) & \varepsilon_{B,t-1}(d_{B,t-1})\varepsilon_{C,t-1}(d_{C,t-1}) & \varepsilon_{C,t-1}^2(d_{C,t-1}) & \varepsilon_{C,t-1}(d_{C,t-1})\varepsilon_{D,t-1}(d_{D,t-1}) & \varepsilon_{C,t-1}(d_{C,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) \\ \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{D,t-1}(d_{D,t-1}) & \varepsilon_{B,t-1}(d_{B,t-1})\varepsilon_{D,t-1}(d_{D,t-1}) & \varepsilon_{C,t-1}(d_{C,t-1})\varepsilon_{D,t-1}(d_{D,t-1}) & \varepsilon_{D,t-1}^2(d_{D,t-1}) & \varepsilon_{D,t-1}(d_{D,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) \\ \varepsilon_{A,t-1}(d_{A,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) & \varepsilon_{B,t-1}(d_{B,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) & \varepsilon_{C,t-1}(d_{C,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) & \varepsilon_{D,t-1}(d_{D,t-1})\varepsilon_{E,t-1}(d_{E,t-1}) & \varepsilon_{E,t-1}^2(d_{E,t-1}) \end{bmatrix}$$

5. Empirical Results

This paper studied financial shock transmission among five sectors of DSE both as return and volatility spillover. BVAR output was used to test return spillover effects while asymmetric versions of GARCH specifications provided volatility spillover among those sectors.

5.1. Return Spillover Analysis

We have used Bayesian VAR to test return spillover effects between companies traded under DSE in sectors like Engineering, Food, Pharmaceuticals, Fuel & Power and Commercial Banks from January, 2009 to January, 2016. Table 5 demonstrates a highly significant memory effect or return from engineering, food, pharmaceuticals and banking sectors influenced by their previous performances. A highly significant return spillover effect is clearly visible from lag 2 return of commercial banking sector to all other sectors whereas only lag 2 returns from engineering and food sector has been found to have highly significant return spillover effect on returns from commercial banking sector. The returns from fuel & power and pharmaceuticals sector has spillover effect on engineering sector only. Pairwise return spillover effects are unidirectional between bank-pharmaceuticals,

engineering-pharmaceuticals, bank-power, and engineering-power sectors. On the other hand, pairwise spillover effects are bidirectional between food-engineering, bank-engineering and bank-food sectors. All these sectorial transmission of return spillovers are taking two days' time lag to affect other sectors in DSE.

5.2. Volatility Spillover using GJR-GARCH

Table 6 represents a highly significant ARCH (α) effect on conditional variance of food industry, fuel & power sector, and commercial banks from GJR-GARCH output. This indicates that news about volatility from previous period innovations or shocks have contributed significantly in predicting next period' conditional variance. Previous period's forecast variance (GARCH- β) or historical volatility also has highly significant effect on conditional variance of all returns except food and pharmaceuticals sectors. Gamma (γ) coefficient indicates a highly significant asymmetric news impact on conditional variance of food, fuel & power and banking sector' returns. In other words, good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} < 0$) have differential effect on those sector returns. The sum of ARCH and GARCH coefficients ($\alpha + \beta$) is very close to one, indicating that volatility shocks are quite persistent or dies out very slowly for commercial bank returns.

Table 5. Return Spillover Test through Bayesian VAR among all Sectors

Regressors	Response Variables				
	Engineering (A)	Food Ind. (B)	PharmaInd (C)	Power & Fuel (D)	Banks (E)
θ	-0.000309	0.000819	0.000106	-0.000887	-0.00127
ω_1	0.016988	0.141218**	0.003994	0.047315	0.0892
ω_2	-0.164166***	-0.216676***	-0.125465**	-0.063889*	0.432***
Return Spillover Coefficients					
δ_1	0.073054	-0.034961	-0.025325	0.024662	-0.02856
δ_2	-0.246298***	-0.097911	-0.041466	0.232259***	-0.1104**
ψ_1	-0.071059	0.006295	-0.011779	-0.002890	-0.000214
ψ_2	-0.080146	-0.071119	0.325454***	-0.070999**	-0.184***
η_1	-0.05464	-0.053161	-0.012741	-0.022909	-0.04345
η_2	-0.019785	0.514737***	-0.100544***	-0.041705	-0.079692
κ_1	0.002695	-0.047263	0.043738	-0.020013	-0.021266
κ_2	0.5798***	-0.098234**	-0.057107	-0.084537*	-0.064424

***, ** and *: level of significance at 1%, 5%, and 10% respectively.

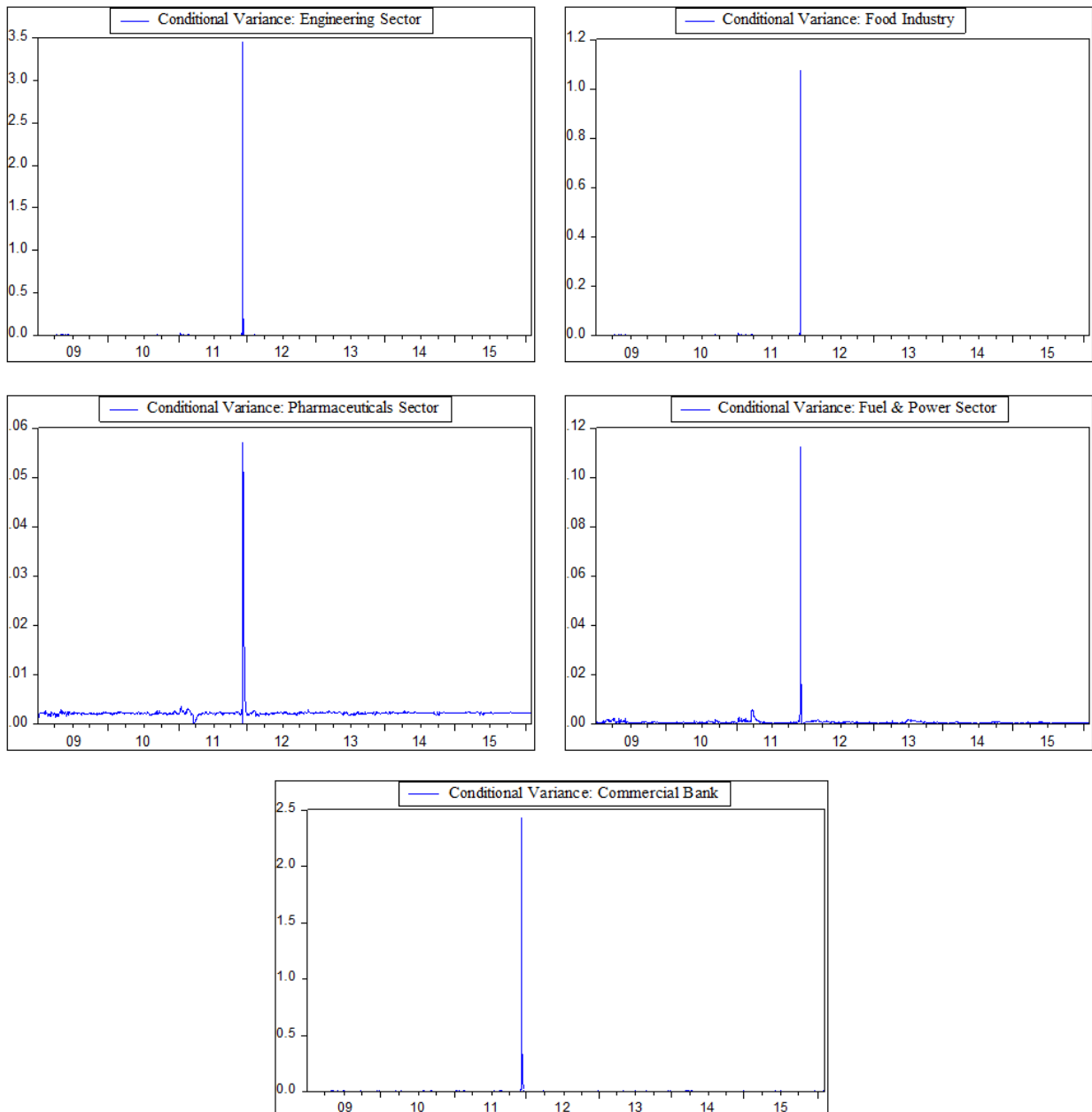


Figure 3. Conditional variance from TGARCH model

Table 6. Conditional Variance Equation with GJR-GARCH

Regressors		Response Variables				
		$\sigma_{A_t}^2$	$\sigma_{B_t}^2$	$\sigma_{C_t}^2$	$\sigma_{D_t}^2$	$\sigma_{E_t}^2$
η		-0.00117***	0.0011***	0.000992	0.00045***	5.86E-06
α		0.001667	0.085055***	0.12229	0.096933***	0.256***
B		0.25166***	0.025005	0.566148*	0.423557***	0.507***
Γ		-0.003323	-0.0873***	-0.133066	-0.099384***	0.6974***
Volatility Spillover Coefficients						
Historical Volatility	ξ_{A1}		0.032259	-0.018159	-0.000356	0.0509***
	ξ_{A2}		0.030273	-0.009275	0.08082***	-0.0387*
	ξ_{B1}	0.170857***		-0.000428	-0.000848	0.0371*
	ξ_{B2}	-0.145311***		-0.000420	0.00059	-0.0331*
	ξ_{C1}	0.499490	-0.2947***		0.021242	-0.05718
	ξ_{C2}	0.222466	-0.2855***		-0.19092*	0.05374
	ξ_{D1}	14.54629**	0.0678	-0.008505		1.216956
	ξ_{D2}	-14.30289**	0.058	-0.008567		-1.170572
	ξ_{E1}	1.696291***	0.56722***	0.026419	0.05453***	
	ξ_{E2}	-1.123552***	-0.368***	-0.002065	-0.03672***	
News about Volatility	φ_{A1}		0.000649	-9.46E-06	-0.002888***	0.000332
	φ_{A2}		0.000540	9.42E-06	0.002369***	-0.000494
	φ_{B1}	0.003849***		-0.000347	0.001207***	-0.000574
	φ_{B2}	0.003395***		0.000443	5.25E-05	0.0012***
	φ_{C1}	0.000713	-0.00217***		-0.000231	-2.47E-05
	φ_{C2}	-0.004823***	0.00106***		0.000424	7.89E-05
	φ_{D1}	0.001198***	-0.001222*	0.000548		0.0004***
	φ_{D2}	-0.003582**	0.000695*	0.000359		-0.000589
	φ_{E1}	-0.002984***	-0.001737**	-0.006108	0.001093*	
	φ_{E2}	0.00132	-0.0012	-0.000535	-0.007614***	
Log likelihood		3763.401	4166.428	3306.403	3984.037	4355.996
DW Stat		1.995377	1.984633	1.987930	1.984461	1.9914
Schwarz Criterion		-4.347713	-4.822701	-3.809118	-4.607744	-5.046

***, ** and *: level of significance at 1%, 5%, and 10% respectively.

Volatility in the form of historical news or innovations and historical conditional variance from food industry, fuel & power and commercial banking sectors has highly significant effect on conditional variance of engineering sector. Pharmaceuticals sectors news about volatility with lag 2 of squared residuals has highly significant negative effect on engineering sector' volatility.

Commercial banks and pharmaceuticals sectors' volatility has highly significant effect on food sector's volatility both in the form of news about volatility and historical conditional variance whereas fuel and power sector has only news impact on food sectors' volatility. Pharmaceuticals sector has been found to remain unaffected by volatility of other sectors. Both engineering and commercial banking sector's volatility resulting due to news impact and historical conditional variance has highly significant effect on fuel & power sector' volatility

whereas only last period's news impact has highly significant effect on fuel and power. Commercial banking sector' volatility has been influenced by volatility from food both as news and historical conditional variance while only historical conditional variance of engineering sector and only news impact of power sectors found to have significant effect on banking sector.

Bi-directional volatility spillover of historical conditional variance and news about volatility is clear between both engineering-power and bank-food sectors pair. Volatility transmission is bidirectional for commercial bank-engineering pair in the form of lag 1 and lag 2 of historical volatility and for food-power and power-banks pairs this spillover is also bidirectional but in the form of historical news about volatility. Conditional variance graphs of Figure 3 clearly demonstrates that all random variations in the series is modelled successfully

by GJR-GARCH except abnormal variations exhibited by all sectors at the end of 2011.

5.3. Volatility Spillover Using Multivariate GARCH

Multivariate GARCH models with diagonal specification fails to identify the direction of spillover i.e. it does not give any indication of whether X has spillover effect on Y or vice-versa, however if covariance is significant between X and Y, we can only guess presence of spillover but without any direction. Diagonal VECH output of Table 7 indicates a highly significant effect of historical volatility (GARCH- β) on predicting next period's conditional variance of all sectors under study while ARCH (α) effect or news impact is highly significant on influencing conditional variance of food, fuel & power, and commercial banking sectors. Gamma

coefficient indicates a highly significant asymmetric news impact on conditional variance of engineering and banking sectors' return series or in other words good news ($\epsilon_{t-1} > 0$) and bad news ($\epsilon_{t-1} < 0$) have differential effect on those sector returns. The sum of ARCH and GARCH coefficients ($\alpha + \beta$) is very close to one, indicating that volatility shocks are quite persistent or dies out very slowly for all sector' return series.

Multivariate GARCH model like Diagonal VECH output at Table 7 clearly reveals highly significant volatility spillover, indicated by covariance or co-volatilities, between all pairs of return series except for engineering-pharmaceuticals pair where co-volatilities between engineering-food, food-pharmaceuticals, and pharmaceuticals-power sectors pair are significantly influenced by only last period' news impact indicated by α . However, co-volatilities of all other return series under study are highly influenced by both ARCH and GARCH effect.

Table 7. Conditional Variance Equation with Diagonal VECH-GARCH

		Engineering (A)	Food Ind. (B)	Pharma Ind (C)	Power & Fuel (D)	Banks (E)
Engineering (A)	α	0.001187	0.019624	0.001179	0.001206***	0.025509***
	β	1.001597***	0.941579***	1.000613	0.000213**	0.802399***
	γ	0.000612***	0.00035	0.00412	0.000121	0.000147
Food Ind. (B)	α		0.324393**	0.019494	0.019940**	0.421683**
	β		0.885157***	0.940653***	0.935272**	0.754317***
	γ		0.00912	0.00085	0.0082	0.00075
Pharma Ind (C)	α			0.001171	0.001198	0.025341**
	β			0.999629***	0.993910***	0.801610***
	γ			3.00E-05	0.00007	0.000532
Power & Fuel (D)	α				0.001226**	0.025920**
	β				0.988224***	0.797024***
	γ				0.00035	0.0127
Banks (E)	α					0.54815***
	β					0.6428***
	γ					0.00762***
Log Likelihood (7549.751); Schwarz criterion (-8.685911)						

***, ** and *: level of significance at 1%, 5%, and 10% respectively.

Table 8. Conditional Variance Equation with Asymmetric Scalar Diagonal BEKK-GARCH

		Engineering (A)	Food Ind. (B)	Pharma Ind (C)	Power & Fuel (D)	Banks (E)
Engineering (A)	α	0.2547***	0.2237**	0.14996***	0.19626***	0.20885***
	β	0.8194***	0.88277***	0.90817**	0.89616**	0.84774**
	γ	0.04864**	0.05373	0.03442	0.03266	0.11741
Food Ind. (B)	α		0.1965***	0.13173	0.1724**	0.18346***
	β		0.8885***	0.91413	0.90204**	0.8533**
	γ		0.05935	0.03802	0.03608	0.12970
Pharma Ind (C)	α			0.08828***	0.11554***	0.12295*
	β			0.94043**	0.92799**	0.8778***
	γ			0.02436	0.02311	0.08309
Power & Fuel (D)	α				0.15122***	0.16092***
	β				0.91572*	0.8662**
	γ				0.0219***	0.07885
Banks (E)	α					0.1712***
	β					0.8194**
	γ					0.2834***
Log Likelihood (20627.62); Schwarz criterion (-24.21202)						

***, ** and *: level of significance at 1%, 5%, and 10% respectively.

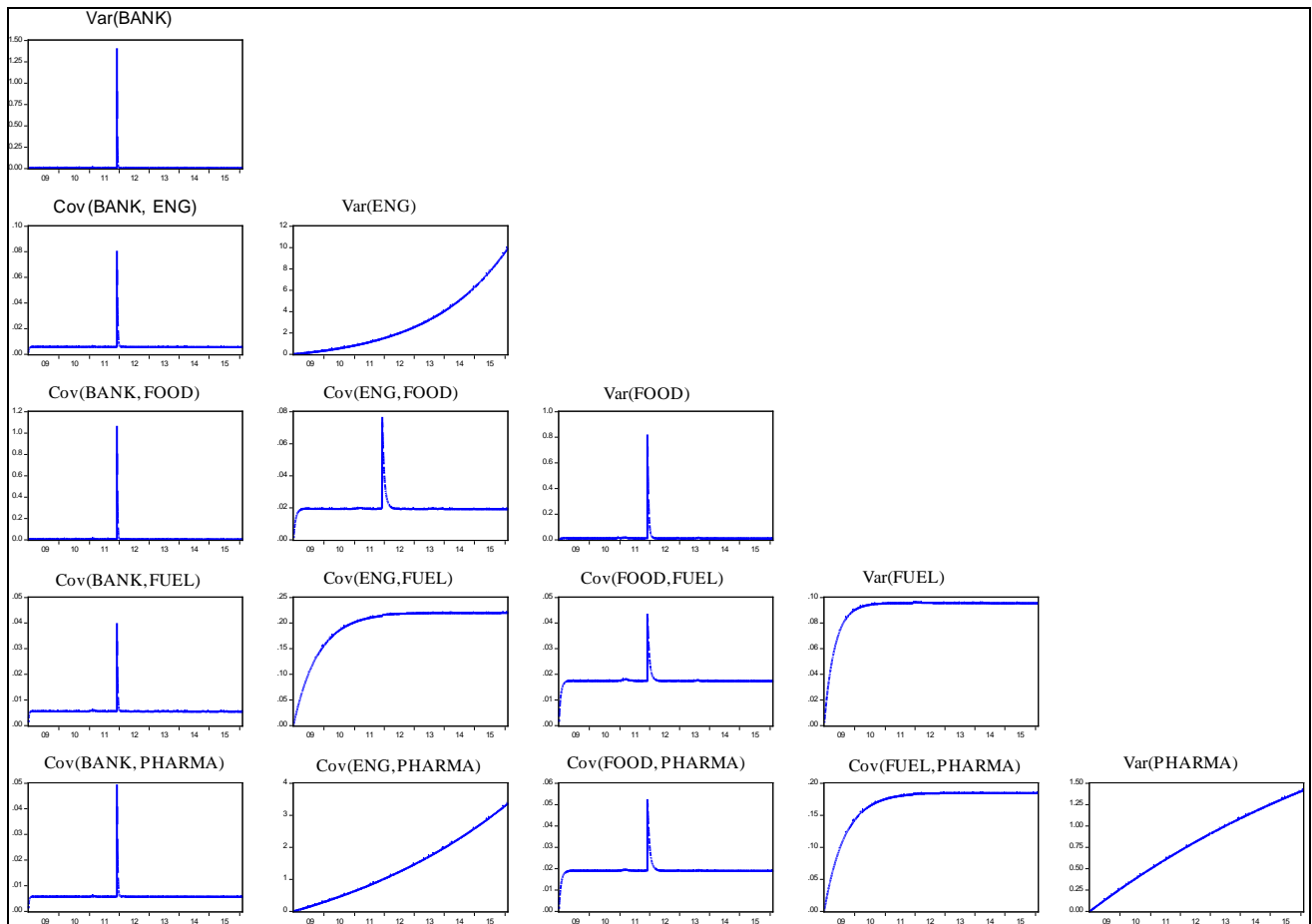


Figure 4. Conditional covariance from diagonal VECH GARCH model

Scalar diagonal BEKK output of Table 8 indicates similar result like diagonal VECH where a highly significant effect of historical volatility and news impact is evident on influencing conditional variance of all sectors under study. Gamma coefficient indicates a highly significant asymmetric news impact on conditional variance of engineering, power and banking sectors' return series or in other words bad news ($\varepsilon_{t-1} < 0$) increases volatility more than good news ($\varepsilon_{t-1} > 0$) on those sector returns. Covariance or co-volatilities between return series of all sectors except for food-pharmaceuticals in Table 8 indicates highly significant volatility spillover both in the form of historical volatility and news impact. Based on Schwarz criteria and log likelihood, scalar diagonal VECH-GARCH provided superior fit compared to similar BEKK specification. VECH specification sketched on Figure 4 successfully modelled co-movement among all sectors except abnormal variation of 2011.

6. Conclusion

Volatility spillover provides useful insights to investors on successful diversification of capital through understanding co-movements and integration dynamics within and across markets. Global investors looking for scope of diversifying portfolio risk in Bangladesh capital market will find this research very useful to understand the volatility and return dynamics of the market. This paper used daily stock index return data of five sectors traded in DSE to examine return spillover effects through

Bayesian VAR model. The conditional mean equations derived from BVAR were used in asymmetric versions of GJR-GARCH, VECH and BEKK GARCH models to identify co-movement among all those sectors.

Bayesian VAR output demonstrates a highly significant memory effect of two days' time lag on all sector returns except for fuel & power sector. Commercial bank sector being the largest sector in DSE has significant return spillover effect on all sectors under study where only engineering and food industry exhibited return spillover effect on commercial banking sector. Bidirectional return spillover is evident between food-engineering, bank-engineering, and bank-food pairs. All return spillovers are taking two days' time lag to affect other sectors of DSE.

GJR GARCH output reveals both memory effect and news impact on volatility of commercial banks and fuel & power sectors whereas news impact is also found to be significant for food industry and memory effect is found to be significant for engineering. Asymmetric effect or impact of negative news increases volatility of all sectors under study except for engineering and pharmaceuticals. Bidirectional volatility spillover is instrumental between bank-food, bank-engineering, bank-power, power-engineering, and power-food sectors whereas pharmaceuticals sector is found to be immune from volatility of other sectors. Scalar diagonal version of VECH and BEKK output identified strong memory effect, news impact and leverage effect on almost all sectors under study. Scalar diagonal VECH reveals highly significant volatility spillover, indicated by co-volatilities, between all sectors under study except for engineering-pharmaceuticals pair. Scalar diagonal BEKK

reveals similar result except that volatility spillover is absent for food-pharmaceuticals pair.

These findings have important implications, specifically for global investors looking to emerging market like Bangladesh to diversify their capital. The findings would help investors understanding the risk involved and way of minimizing it through diversifying capital among less integrated sectors of the market. The analysis could be extended further in future by employing a full multivariate GARCH model to identify direction of spillover or researchers could identify jump spillover by incorporating stochastic volatility models.

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