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Information Flows between Sectors in Indian Stock Markets[1]

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Abstract

The paper investigates return and volatility spillover mechanism between ten sectors of the Bombay Stock Exchange in India. The study uses cointegration analysis to examine the co-movements between different sectors prices and VAR analysis to investigate the transmission of shocks between different sector returns. A bivariate GARCH model is also used to estimate the volatility spillover mechanism. The findings of the study indicate that there are strong information flows between sectors. The findings have significant implications for investors as well as policymakers.

Key words: Information flows, Volatility spillover, Cointegration, Granger causality, Bivariate GARCH

JEL classification: C15, G1

I. INTRODUCTION

Globalization has resulted in more integration of international financial markets and financial market participants are interested in knowing how shocks and volatility are transmitted across markets over time. There are generally two main lines of research in this context; the first one is the cointegration analysis which was originally used by Kasa (1992) to investigate the transmission of shocks among stock prices and stock returns. This approach is normally adopted to study the co-movements between different international financial markets over a long period of time. The second line of research is to study the mechanism of volatility spillover between different markets associated to each other. Researchers have mostly used the Multivariate GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models to examine the persistence and transmission of volatility from one market to other markets.

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[1] *Invited Article*

The shocks and volatility transmission mechanism are extensively studied in the literature [see Booth et al. (1997) and Huang et al. (2000) for a review of recent studies], but the major focus has been on either the linkages between stock markets of different countries or different types of financial markets within a given country. A few of the existing research have addressed the issue of return and volatility linkages between sectors within a given stock market, however. Studying the pattern of returns and volatility between sectors and how they may interact with each other is important for the efficient asset allocation decisions and empirical modeling of sector returns. This paper proposes to fill this gap in the literature by examining the return and volatility linkages at the sector level in Indian stock markets. In doing so the study investigates the transmission of shocks and volatility spillover mechanism between the sectors of Bombay Stock Exchange (BSE) in India. Specifically, we employ cointegration analysis to study the co-movements between different sectors' price indexes and vector auto regressive (VAR) analysis to investigate the transmission of shocks between different sector returns. We also use a bivariate GARCH model to estimate the volatility spillover mechanism. Such an investigation of the pattern of information flows at the sector level should be important, as individual and institutional investors often use sector indexes as a benchmark to track the performance of actively managed portfolios (Ewing, 2002; Ewings, Forbes, & Payne, 2003). The findings of the study have also significant implications for policy makers such as central bank concerning the "contagion" of volatility between sectors.

The rest of the paper is organized as follows. In the following section, we review the literature. In section 3, we outline the data and methodology of the study. Section 4 presents the empirical results and finally, Section 5 concludes the study with policy implications.

II. LITERATURE REVIEW:

There is a large body of literature assessing co-integration and volatility spillover across financial markets from different countries. The literature is so voluminous that it would not be feasible here to provide a detailed review. Hence we would mention here only some of the important studies. Kasa (1992) estimates an error-correction VAR model and computes a common stochastic trend in the equity markets of the US, Japan, Britain, Germany and Canada. Jeon and Chiang (1991) investigate the behaviour of stock prices in New York, London, Tokyo and Frankfurt based on univariate and multivariate cointegration approaches. Chan et al. (1991), Arshanapalli et al. (1995) and Ghosh et al. (1999) examine the stock price movements between the US and Asian equity markets using cointegration methods. Chen, Firth, and Rui (2002) investigate the dynamic interdependence of the major markets in Latin America using cointegration analysis and error correction vector autoregressions (VAR) techniques.

Substantial attention has also been focused on how news from one market affects the volatility process of another market. See, for instance, Hamao, Masulis, and Ng (1990), Koutmos and Booth (1995), and Lin, Engle, and Ito (1994) in the U.S., U.K., and Japanese stock markets; Booth, Martikainen, Tse (1997) and Christofi and Pericli (1999) in other international stock markets. All these articles use the GARCH-type models to examine the volatility spillovers between markets. The theory of volatility spillovers based on the GARCH models is first introduced and named "meteor showers" by Engle, Ito, and Lin (1990). Chan, Chan, and Karolyi (1991) provide a detailed discussion on the need to focus on the volatility spillovers between the stock and futures markets. In particular, following Ross (1989), Chan, Chan, and Karolyi contend that "it is the volatility of an asset's price, and not the asset's simple price change, that is related to the rate of flow of information to the market."

Though there is a voluminous literature assessing co-integration and volatility spillover across financial markets from different countries, a very meager coverage of the same across different markets or sectors within the same country. Squalli, J (2007) investigates cointegration and causality across the common sectors of the Abu Dhabi Securities Markets and the Dubai Financial Markets. Ewing (2002) using generalized forecast error variance decomposition technique within a vector auto regression framework analyzes the interrelation among five major S&P stock indexes. Using monthly data from January 1988 to July 1997, he finds that unanticipated 'news' or shocks in one sector have significant impact on other sector returns. Ewing, Forbes, and Payne (2003) study the effects of macroeconomic shocks on five major S&P sector-specific stock markets for the post-1987 crash period. Using generalized impulse response analysis, they show that individual asset prices are influenced more by unanticipated macroeconomic events as compared with some predictable events. Wang, Kutan, and Yang (2005) examine the patterns of information flows within and across sectors of two Chinese stock exchanges in Shanghai and Shezhan during 1994-2001. Using the generalized forecast variance decomposition, they find a high degree of interdependence, indicating that the sectors are highly integrated and sector prices reflect information from other sectors. Fornari, Monticelli, Pericoli, and Tivegna (2002) used a trivariate GARCH model to analyse the impact of political and economic 'news' on conditional volatility of several Italian financial variables. They find a significant regime shift and seasonal daily pattern in the unconditional variance of variables under study. Hassan and Malik (2007) employ a multivariate GARCH model to simultaneously estimate the mean and conditional variance using daily returns among different US sector indexes from January 1, 1992 to June 6, 2005. They find significant transmission of shocks and volatility among different sectors. In my knowledge there is no study investigating return and volatility linkages between sectors in Indian stock markets. Hence an attempt is made in the present study to fill up the gap in this direction.

III. DATA AND METHODOLOGY

3.1. Data, sample period, and descriptive statistics

We employ BSE daily sector price indices that are obtained from Prowess database. The dataset consists of ten sectors: Automobile, Bank, Capital Goods, Consumer Durable, FMCG, Healthcare, IT, Metal, Oil & Gas, and PSU. In order to obtain a consistent sample range for all the sectors indices, we have restricted the sample size for a period from August 23, 2004 to March 27, 2008, with a total of 902 daily observations. The daily sector price series are presented in Figure 1 and the daily sector return series ($R_{i,t}$)[1] are shown in Figure 2.

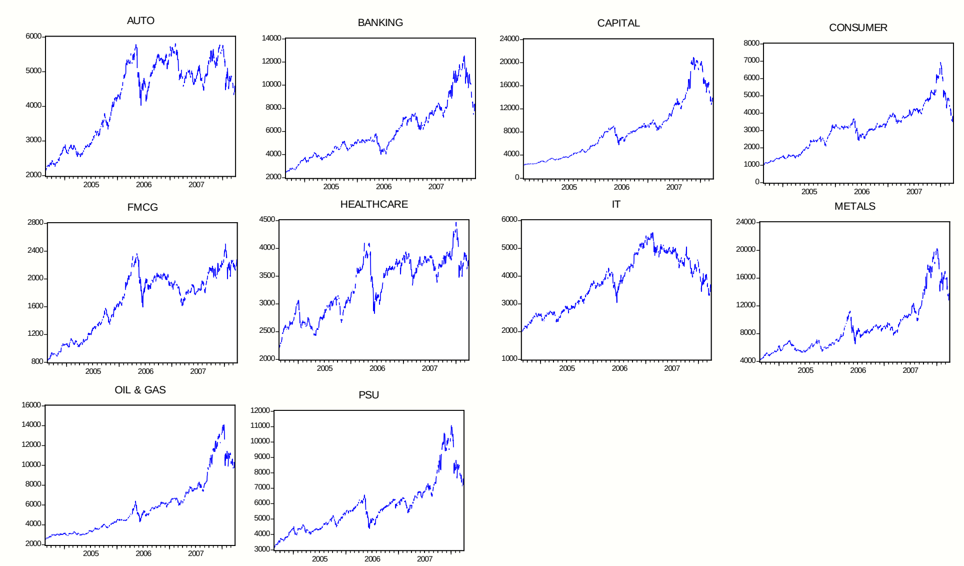

Figure 1: Sector Price Series

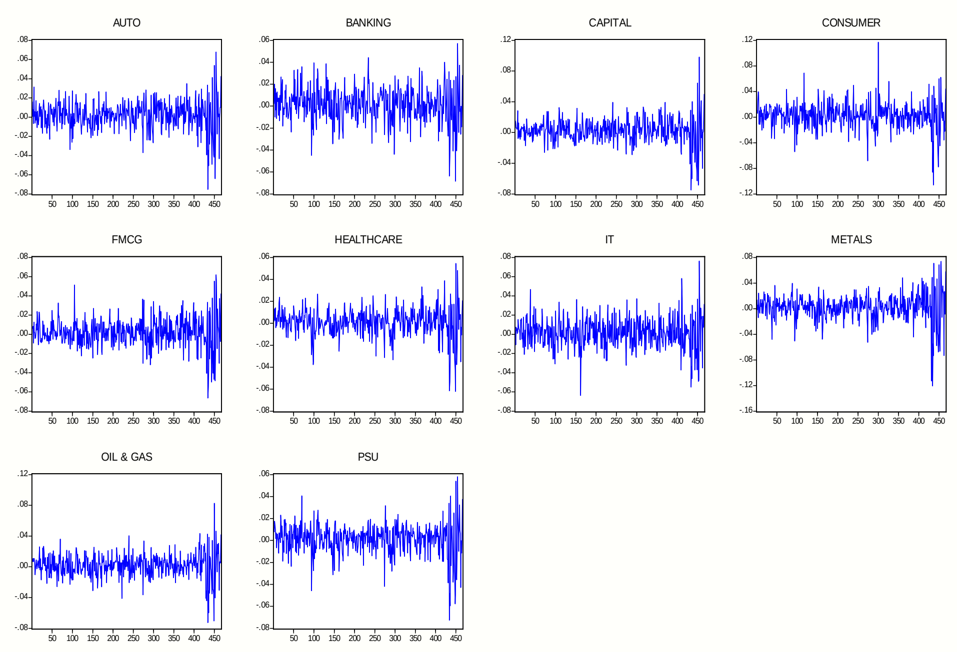

Figure 2: Sector Return Series

In Table I, we report the descriptive statistics for daily returns $R_{i,t}$. The results show that the Automobile sector has the lowest return (0.08%), and the Capital Goods sector has the highest (0.2%), followed by Oil & Gas sector (0.15%) and Consumer Durable sector (0.14%). Metal sector shows the largest standard deviation (2.2%), followed by Consumer Durable (2.0%). The measures for skewness indicate that the return series are negatively skewed for almost all sectors, a common feature in international stock markets. Only IT sector return series are positively skewed. Also, the excess kurtosis measures show that all the series are leptokurtic. The evidence shows that the return series are not normally distributed which is also supported by the Jarke-Bera statistics. Furthermore, the Ljung-Box tests on squared returns reveal a strong and significant deviation from normality, indicating the presence of ARCH effects which is also evident from the volatility clustering observed in Figure 2. These results are thus in favour of a model that incorporates ARCH/GARCH features to capture the volatility clustering.

TABLE - I

Descriptive statistics of returns

	Mean	Median	SD	Skewness	Kurtosis	Jarke-Bera	$LB^2(36)$
BSE							
Auto	0.00082	0.00173	0.015	-0.73483	6.9882	678.2	326.664
Bank	0.00133	0.00183	0.018	-0.34022	5.3254	220.4	235.348
Capital goods	0.00201	0.00284	0.018	-0.25609	6.4726	462.5	594.181
Consumer durable	0.00147	0.00235	0.020	-0.37734	7.3619	735.7	202.966
FMCG	0.00112	0.00160	0.015	-0.34856	5.5998	272.0	691.265
Healthcare	0.00059	0.00148	0.013	-0.92605	7.7597	979.3	421.441
IT	0.00063	0.00034	0.017	0.09080	4.9058	137.6	334.172
Metal	0.00131	0.00296	0.022	-082001	7.6400	909.2	518.193
Oil & Gas	0.00154	0.02426	0.018	-0.68174	9.3651	1590	606.775
PSU	0.00097	0.00265	0.016	-0.87436	8.4146	1215	538.545

3.2. Methodology

3.2.1. Cointegration

Regressing non-stationary variables on each other leads to potentially misleading inferences about the estimated parameters and the degree of association. Therefore, before testing for cointegration, the order of integration of price series must be determined. To identify whether our series are I(1), we employ both the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and the Phillips - Perron (P-P) test (1988). If each price series is an I(1) process, the series can be modeled by cointegration analysis.

The concept of cointegration was first introduced by Granger (1981). Engle and Granger (1987) propose a procedure for testing the cointegration hypothesis. A levels-regression is performed to generate residuals which may be thought of as equilibrium pricing errors. Residuals are then subjected to tests for cointegration.

The Augmented Dickey-Fuller (ADF) test for cointegration is used for this purpose. With two time series - X_t and Y_t, each of which is I(1), the cointegration regression equation is

$$X_t = \eta_0 + \eta_1 Y_t + s_t \qquad \ldots \quad (1)$$

Now the price series will be cointegrated if and only if s_t is stationary.

Tests for cointegration proposed by Engle and Granger (1987) rely on a superconvergence result and apply an OLS estimation to obtain parameter estimates of the cointegrating vector. Johansen (1988, 1991) and Johansen and Juselius (J-J) (1990) derive maximum likelihood estimators of the cointegrating vectors for an autoregressive process with independent Gaussian errors and a likelihood ratio test for the number of cointegrating vectors. Their procedure has the advantage of taking into account the error structure of the underlying process. It can incorporate different short and long-run dynamics of a system of economic variables. It enables us to estimate and test the equilibrium relationship among non-stationary series while abstracting from short-term deviations from equilibrium. Thus, it provides relatively powerful tests when the model is correctly specified.

The J-J procedure is completed by estimating the following equation using a VAR

$$\Delta x_t = \gamma x_{t-1} + \sum_{i=1}^{n} \delta_i \Delta x_{t-i} + \varepsilon_t \qquad \ldots. \quad (2)$$

where x_t and ε_t are vectors and γ is a matrix of parameters. The rank of the matrix is tested and the parameters are estimated via maximum likelihood. The following statistics are derived:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} I_n (1 - \hat{\lambda}_i) \qquad \ldots. \quad (3)$$

$$\lambda_{max}(r, r+1) = -T\, I_n (1 - \hat{\lambda}_{r+i}) \qquad \ldots. \quad (4)$$

where $\lambda_{trace}(r)$ is the trace statistic, $\lambda_{max}(r, r+1)$ is the eigen-max statistics, $\hat{\lambda}_i$ denotes the estimated eigenvalues and T is the number of usable observations. The null hypothesis tested in λ_{trace} (r) is for no cointegration. In fact, for bivariate cointegration tests, up to two null hypotheses can be tested. If the null that r = 0 is rejected at least one cointegrating vector may exist and the second hypothesis that r ≤ 1 is subsequently tested.

For 0 < r < n, there exist r cointegrating vectors.

As long as the series have a common trend, causality (in the temporal Granger sense), must exist in at least one direction either unidirectional or birectional. However, although cointegration indicates the presence or absence or Granger-Causality, it does not indicate the direction of causality between variables. This can be addressed using a Granger Causality test as described in the next section.

3.2.2. Granger Causality Tests

Granger Causality (GC) tests attempt to identify whether fluctuations in a particular market affect another market. They represent a crucial supplement to cointegration tests by determining the specific direction of the causation flow. The GC test can be completed by running the following bi-variate regressions:

$$x_t = \sum_{i=1}^{p} \alpha_i x_{t-1} + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_t \qquad \text{.........} (5)$$

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-1} + \sum_{i=1}^{p} \beta_i x_{t-i} + \varepsilon_t \qquad \text{..........} (6)$$

where x_t (y_t) is assumed to be a function of past values of itself and past and contemporaneous values of y_t (x_t) and where x_t and y_t represent return series. The standard F-test is used to examine Granger-causality between variables in the VAR system. If the F-test rejects the null hypothesis that the lag coefficients of variable y in equation (5) are jointly zero, we then can say that variable y Granger causes variable x. Similarly, if the null hypothesis that the lag coefficients of variable x in equation (6) are jointly zero, the variable y Granger causes variable x.

3.2.3. Univariate ARCH and GARCH Models

Let the return series R_t be defined as

$$R_t = E(R_t / \Psi_{t-1}) + \varepsilon_t \qquad \text{-----} \ (7)$$

where, E (R_t / Ψ_{t-1}) is the conditional expected return at time *t* given the information set Ψ_{t-1} at time *t-1*, and the residual or shock term ε_t is the unexpected return at time *t* .

Bollerslev (1986) generalizes the ARCH (q) model introduced by Engle (1982), to the GARCH (p, q) model for the conditional variance of return, h_t, such that

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + .. + \alpha_q \varepsilon_{t-q}^2 + \beta_1 h_{t-1} + \beta_2 h_{t-2} + .. + \beta_p h_{t-p} \quad \ldots (8)$$

where $\omega > 0$, $\alpha_1, \alpha_2, \ldots, \alpha_q \geq 0$, $\beta_1, \beta_2, \ldots, \beta_p \geq 0$. The GARCH (p, q) process defined above is stationary when $(\alpha_1 + \alpha_2 + \ldots + \alpha_q) + (\beta_1 + \beta_2 + \ldots + \beta_p) < 1$.

3.2.4. Multivariate GARCH

To examine the volatility transmission among different sectors, we use BEKK parameterizations[2] of MGARCH developed by Engle and Kroner (1993). The BEKK parameterization is given as:

$$H_t = C' C + \sum_{i=1}^{m} A'_i (\varepsilon_{t-i} \varepsilon'_{t-i}) A_i + \sum_{j=1}^{m} B'_j H_{t-j} B_j , \quad \ldots..(9)$$

where C, A and B are n x n matrices and C is a lower triangular.

This can be expressed for the bivariate case of the BEKK as:

$$\begin{bmatrix} H_{11,t} & H_{12,t} \\ H_{21,t} & H_{22,t} \end{bmatrix} = C' C + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} H_{11,t-1} & H_{12,t-1} \\ H_{21,t-1} & H_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \quad \ldots.(10)$$

where c_{ij} are elements of a 2 x 2 symmetric matrix of constants C, the elements a_{ij} of the symmetric 2 x 2 matrix A_i measure the degree of innovation from index *i* to index *j*. More particularly, the elements a_{ij} for $i \neq j$ measure the degree of innovation from *i* to *j* and from *j* to *i* index, respectively. The elements b_{ij} of the symmetric 2 x 2 matrix B_j indicate the persistence in conditional volatility between *i* index and *j* index. Alternatively, the elements b_{ij} for $i \neq j$ in conditional variance equation (10) measure the volatility spillover from *i* to *j* and from *j* to *i* index, respectively. The total number of estimated elements for the variance equations is n(5n+1)/2. In our bivariate case the number of elements is 2(5x2+1)/2 = 11.

The conditional variance for each equation, ignoring the constant terms, can be expanded for the bivariate GARCH (1, 1) as:

$$h_{1,t} = a_{11}^2 e_{1,t-1}^2 + 2a_{11}a_{21}e_{1,t-1}e_{2,t-1} + a_{21}^2 e_{2,t-1}^2 + b_{11}^2 h_{1,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{2,t-1} \quad \text{...(11)}$$

$$h_{2,t} = a_{12}^2 e_{1,t-1}^2 + 2a_{12}a_{22}e_{1,t-1}e_{2,t-1} + a_{22}^2 e_{2,t-1}^2 + b_{12}^2 h_{1,t-1}^2 + 2b_{12}\, b_{22}h_{12,t-1} + b_{22}^2 h_{2,t-1}^2 \quad \text{...(12)}$$

With the assumption that the random errors are normally distributed, the log-likelihood function for the MGARCH model is:

$$L(\theta) = -\frac{Tn}{2} + \ln(2p) - \frac{1}{2}\sum_{t=1}^{T} (\ln \left| H_t \right| + \varepsilon'_t \left| H_t^{-1} \right| \varepsilon_t \quad \text{...(13)}$$

where T is the number of observations, n is the number of indices, θ is the vector of parameters to be estimated, and all other variables are as previously defined. The BHHH (Berndt, Hall, Hall and Hausman) algorithm is used to produce the maximum likelihood parameter estimates and their corresponding asymptotic standard errors.

IV. EMPIRICAL RESULTS

4.1. Stationary and Cointegration Test

Two standard procedures are applied to establish the nonstationarity of each individual log price series. The null hypothesis for both procedures is that a unit root exists. One is the augmented Dickey-Fuller test, and the second procedure is the Phillips-Perron test. Table II reports results for I(1) versus I(0) (level prices), applying the two tests. The results indicates that there is one unit root in each of the log price indexes under study, but no unit root in their first differences at the 5% significance level. Because we find that the level of the each series is an I(1) process, and accordingly, they can wonder extensively, we need to consider possible cointegration relation between them.

Table II

Test for Stationarity of log prices and return series

	Log prices		Returns	
	ADF (prob)	PP(prob)	ADF (prob)	PP(prob)
BSE				
Auto	-2.155 (0.223)	-2.247 (0.189)	-26.798 (0.000)	-26.739 (0.000)
Bank	-1.866 (0.348)	-1.881 (0.341)	-25.133 (0.000)	-24.850 (0.000)
Capital goods	-1.483 (0.541)	-1.557 (0.504)	-25.845 (0.000)	-25.742 (0.000)
Consumer durable	-2.352 (0.156)	-2.382 (0.147)	-27.040 (0.000)	-27.055 (0.000)
FMCG	-2.064 (0.259)	-2.045 (0.267)	-28.571 (0.000)	-28.581 (0.000)
Healthcare	-2.364 (0.152)	-2.386 (0.146)	-26.549 (0.000)	-26.660 (0.000)
IT	-2.230 (0.190)	-2.260 (0.180)	-28.987 (0.000)	-29.054 (0.000)
Metal	-1.300 (0.620)	-1.260 (0.640)	-26.753 (0.000)	-26.738 (0.000)
Oil & Gas	-0.780 (0.820)	-0.780 (0.640)	-28.175 (0.000)	-28.120 (0.000)
PSU	-1.836 (0.362)	-1.860 (0.351)	-26.188 (0.000)	-26.057 (0.000)

Johansen's (1991) multivariate cointegration test is used to investigate whether the sectoral indices in BSE are cointegrated. The analysis of the appropriate rank of the cointegration vectors is presented in Table III. The optimal lag length chosen is two following AIC and SC. The null hypothesis that the sectoral indices are not cointegrated (r=0) against the alternative of one or more cointrgrating vectors (r > 0) is not rejected since the λ_{trace} (0) and λ_{max} (0) statistics do not exceed their critical values at the 5% significant level. Thus, following Johansen's (1991) test, we find no evidence of cointegration in sectoral indices in BSE. This means there is no specific long-term relationship between them that has to be modeled with an error correction framework.

Table III

Johansen Multivariate Cointegration Tests

	Trace Test			Max-Eigen Test		
	Trace Statistic	0.05 Critical value	Prob.	Max-Eigen Statistic	0.05 Critical value	Prob.
$\Pi = 0$	219.2465	239.2354	0.2732	53.96402	64.50472	0.3448
$\Pi \leq 1$	165.2824	197.3709	0.5989	47.16037	58.43354	0.4037
$\Pi \leq 2$	118.1221	159.5297	0.8828	31.02176	52.36261	0.9444
$\Pi \leq 3$	87.10030	125.6154	0.9154	26.89300	46.23142	0.9198
$\Pi \leq 4$	60.20731	95.75366	0.9479	18.50520	40.07757	0.9887
$\Pi \leq 5$	41.70211	69.81889	0.9174	13.65565	33.87687	0.9917
$\Pi \leq 6$	28.04645	47.85613	0.8117	10.84619	27.58434	0.9692
$\Pi \leq 7$	17.20026	29.79707	0.6252	7.298873	21.13162	0.9412
$\Pi \leq 8$	9.901388	15.49471	0.2884	5.138646	14.26460	0.7242
$\Pi \leq 9$	4.762742	3.841466	0.0291	4.762742	3.841466	0.0291

The statistics of Trace Test and Max-Eigen Test reported in the table are derived using the following equations:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} I_n (1 - \hat{\lambda}_i) \qquad \ldots. \quad (3)$$

$$\lambda_{max}(r, r+1) = -T\ I_n\ (1 - \hat{\lambda}_{r+i}) \qquad \ldots. \quad (4)$$

where λ_{trace} (r) is the trace statistic, λ_{max} (r, r+1) is the eigen-max statistics, $\hat{\lambda}_i$ denotes the estimated eigenvalues and T is the number of usable observations.

4.2. Causality Test

Since we have ten sectors in BSE under investigation, there are forty five different possible combinations of ten sectors taken two at a time. Table 4 presents Granger causality test results of forty five pairs obtained by VAR estimation using equations (5) and (6). The optimal lag length chosen for the VAR estimation is two. As reported in table 4 (see appendix), the null hypotheses in sixteen out of ninety cases are rejected. The results indicate that Automobile sector Granger causes only Consumer Goods and Healthcare. Banking sector Granger Causes four sectors such as Capital Goods, FMCG, Oil & Gas and PSU, and is Granger caused by only FMCG sector. Similarly Healthcare leads the returns of Bank, IT, Metal and Oil & Gas, while the Capital Goods sector leads the returns of Healthcare and Oil & Gas. The Oil & Gas sector influences the returns of IT as well as Metal. The PSU does Granger cause only Oil& Gas.

4.3. Measuring Volatility Spillover

As mentioned earlier, we have ten sectors in BSE under investigation. We would proceed to investigate the volatility spillover between any two sectors at a time. Since there are forty five different possible combinations of ten sectors taken two at a time, we investigate the volatility spillover of forty five pairs of sectors with the estimation of forty five bivariate GARCH models each containing two sectors.[3] Coefficients of importance in the bivariate BEKK (1, 1) model are a_{ij} and b_{ij}. These coefficients quantify the effects of the lagged own and cross innovations and lagged own and cross volatility persistence on the present own volatility of the two sector indexes. For the brevity we report only b_{ij} estimation for each variance equation in Table 5 (see appendix). The b_{ij}, for $i = j$ parameters indicate that own volatility persistence is very high and significant. In terms of the cross-volatility effects, we explain below the b_{ij}, for $i \neq j$ which indicate the volatility spillover between i index and j index.

The persistent volatility spillover is significant between many sectors. The important sectors are PSU, Oil & Gas, Bank, IT and capital goods. These are the sectors from where volatility spills over to maximum numbers of other sectors.

Similarly, volatility spills over from many sectors to these sectors. The PSU is the only sector from where volatility spills over to all other sectors, while volatility of capital goods sector spills over to the PSU. The next important sector is the Oil & Gas which influences the volatility of Healthcare, IT, Metal, Bank, Consumer and FMCG sectors. On the contrary the volatility of the Oil & Gas is influenced by Auto, Consumer, Metal and PSU sectors. Another important sector is the IT whose volatility spills over to five sectors: Healthcare, Auto, Bank, Capital Goods and FMCG and the volatility of IT is influenced by Healthcare, Metal, Oil & Gas, PSU, Capital Goods and Bank. The next important sector is the Bank whose volatility spills over to Consumer, FMCG, Healthcare, Auto, and IT sectors and the volatility of Bank is influenced by Auto, IT and Metal besides Oil & Gas and PSU. Two way volatility spillovers are also observed between Capital Goods and PSU, Capital Goods and IT and the Capital Goods and Metal. While the volatility spills over from IT, Metal, and Oil & Gas sectors to Auto Sector, volatility of Healthcare spills over to Metal.

For the diagnostic check on the behaviour of squired standardized residuals, the multivariate extension of the univariate Ljung-Box test, i.e. a multivariate portmanteau test is also reported in the last column of the table. The multivariate test statistics is significant for the 38 out of 45 sets which suggest that the models are well specified in most of the cases.

V. SUMMARY AND POLICY IMPLICATIONS

This paper examines the return and volatility linkages at the sector level using daily data from the Indian stock markets. In doing so the study investigates the transmission of shocks and volatility spillover mechanism between sectors in BSE. Specifically, we employ cointegration analysis to study the co-movements between different sectors prices and VAR analysis to study the transmission of shocks between different sector returns. We also use a bivariate GARCH model to estimate the volatility spillover mechanism.

Using Johansen's (1991) trace test, we found no evidence of cointegration in different sectors in BSE, at the 5% significance level. The Granger causality tests for the BSE indexes indicate that Auto sector Granger causes only Consumer Goods and Healthcare. Banking sector Granger Causes four sectors such as capital Goods, FMCG, Oil & Gas and PSU, and is Granger caused by only FMCG sector. Similarly Healthcare leads the returns of Bank, IT, Metal and Oil & Gas, while the capital Goods sector leads the returns of Healthcare and Oil & Gas. The Oil & Gas sector influences the returns of IT as well as Metal. The PSU does Granger cause only Oil& Gas.

To investigate the volatility transmission between sectoral indices in BSE we measure the volatility spillover of forty five pairs of sectors with the estimation of forty five bivariate GARCH models each containing two sectors. The persistent volatility spillover is significant between many sectors. The important sectors are PSU, Oil & Gas, Bank, IT and capital goods. These are the sectors from where volatility spillover to maximum numbers of other sectors. Similarly, volatility spills over from many sectors to these sectors.

The findings of the study indicate that there are strong information flows between different sectors in Indian stock markets. The findings have significant implications for investors as well as policymakers. By uncovering the hidden dynamics of transmission channels among sectors, this research has shown that sectors do interact with each other in terms of shocks and volatility. This implies that investors should keep a close eye on all sectors because a 'news' impacting a certain sector will eventually impact all sectors through their interdependence. Given the significant linkage across sector returns, our results suggest that investors could (partly) predict index movements for a given sector using information flows from other sectors. Hence our findings are useful for institutional and individual investors that are interested in modeling sector movements in Indian stock markets. Moreover, our evidence suggests that potential diversification benefits from sector level investment within the BSE may also be relatively limited, in the light of the significant linkages found among sectors within the market.

From policy makers' perspective, the results suggest that financial trouble in one sector could easily spread to others. The transmission of shocks in one sector to others might create financial market instability during crisis, which could further spread to the production side of the economy. Policy makers could therefore design policies to improve non-influential sectors to prevent the potential negative transmission of shocks from the influential sector to others. On the other hand, it might also be undesirable to directly regulate the influential sector because it is a good source of information for other sectors and it spreads information faster.

Notes

1. The daily returns $R_{i,t}$ is calculated as $R_{i,t} = l_n [P_{i,t} / P_{i,t-1}]$, where $R_{i,t}$ denotes the continuously compounded return for index *i* at time *t* , l_n is the natural logarithm, and $P_{i,t}$ denotes the price level of index *i* at time *t*.
2. The BEKK model is after Baba, Engle, Kraft and Kroner who wrote the preliminary version of Engle and Kroner (1993)
3. An attempt has been made to investigate volatility spillover using ten variate GARCH. However, the maximization process of the likelihood has not converged, which may be due to a very large number of unknown parameters of the ten variate GARCH. In fact, it is not surprising that these models are rarely used when the number of dimensions is larger than four or five. Hence, we have tried to investigate the volatility spillover between sectors using bivariate GARCH model for 45 pairs of series.

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Appendix

Table IV

Granger Causality Test

Null Hypothesis	F-Statistic	Probability
Bank does not Granger Cause Auto	2.65002	0.07119
Auto does not Granger Cause bank	1.00754	0.36553

Capital Goods does not Granger Cause Auto	0.80483	0.44749
Auto does not Granger Cause Capital Goods	1.71497	0.18056
Consumer goods does not Granger Cause Auto	0.06009	0.94168
Auto does not Granger Cause Consumer goods	4.63647	0.00993*
FMCG does not Granger Cause Auto	0.02602	0.97431
Auto does not Granger Cause FMCG	2.32396	0.09848
Healthcare does not Granger Cause Auto	1.56626	0.20940
Auto does not Granger Cause Healthcare	6.06560	0.00242*
IT does not Granger Cause Auto	0.00539	0.99462
Auto does not Granger Cause IT	0.14618	0.86402
Metal does not Granger Cause Auto	0.72473	0.48474
Auto does not Granger Cause Metal	0.30879	0.73442
Oil & Gas does not Granger Cause Auto	1.85039	0.15778
Auto does not Granger Cause Oil & Gas	2.76679	0.06340
PSU does not Granger Cause Auto	0.19150	0.82576
Auto Goods does not Granger Cause PSU	0.20309	0.81624
Capital Goods does not Granger Cause Bank	1.31976	0.26772
Auto does not Granger Cause Capital Goods	3.52023	0.03000*
Consumer goods does not Granger Cause Bank	2.68364	0.06886
Bank does not Granger Cause Consumer goods	2.26052	0.10489
FMCG does not Granger Cause Bank	3.91427	0.02030*
Bank does not Granger Cause FMCG	5.53085	0.00410*
Healthcare does not Granger Cause Bank	5.11834	0.00616*
Bank does not Granger Cause Healthcare	2.45505	0.08644
IT does not Granger Cause Bank	0.64554	0.52462
Bank does not Granger Cause IT	0.93173	0.39425
Metal does not Granger Cause bank	2.21312	0.10996
Bank does not Granger Cause Metal	1.66215	0.19032

Oil & Gas does not Granger Cause bank	2.37070	0.09400
bank does not Granger Cause Oil & Gas	7.06432	0.00090*
PSU does not Granger Cause Bank	0.97411	0.37793
Bank Goods does not Granger Cause PSU	3.44300	0.03239*
Consumer goods does not Granger Cause Capital Goods	0.89573	0.40868
	2.00632	0.13509
Capital Goods does not Granger Cause Consumer goods	0.21773	0.80438
FMCG does not Granger Cause Capital Goods	0.92091	0.39853
Capital Goods does not Granger Cause FMCG	3.00259	0.05016
Healthcare does not Granger Cause Capital Goods	3.34413	0.03573*
Capital Goods does not Granger Cause Healthcare	1.05720	0.34786
IT does not Granger Cause Capital Goods	1.99057	0.13722
Capital Goods does not Granger Cause IT	0.08585	0.91774
Metal does not Granger Cause Capital Goods	0.13459	0.87409
Capital Goods does not Granger Cause Metal	1.88310	0.15272
Oil & Gas does not Granger Cause Capital Goods	3.91593	0.02026*
Capital Goods does not Granger Cause Oil & Gas	0.89283	0.40986
PSU does not Granger Cause Capital Goods	0.21933	0.80310
Capital Goods does not Granger Cause PSU	0.80625	0.44685
FMCG does not Granger Cause Consumer Goods	0.08446	0.91901
Consumer Goods does not Granger Cause FMCG	0.09749	0.90712
Healthcare does not Granger Cause Consumer Goods	0.35555	0.70089
Consumer Goods does not Granger Cause Healthcare	0.25562	0.77449
IT does not Granger Cause Consumer Goods	0.53837	0.58389
Consumer Goods does not Granger Cause IT	2.63799	0.07206
Metal does not Granger Cause Consumer Goods	1.14254	0.31947
Consumer Goods does not Granger Cause Metal	1.72441	0.17887
Oil & Gas does not Granger Cause Consumer Goods	1.48740	0.22652

Consumer Goods does not Granger Cause Oil & Gas	1.80959	0.16432
PSU does not Granger Cause Consumer Goods	1.09550	0.33482
Consumer Goods does not Granger Cause PSU	0.06414	0.93788
Healthcare does not Granger Cause FMCG	0.04964	0.95157
FMCG Goods does not Granger Cause Healthcare	0.01818	0.98199
IT does not Granger Cause FMCG	2.10208	0.12281
FMCG does not Granger Cause IT	2.08426	0.12500
Metal does not Granger Cause FMCG	0.61684	0.53988
FMCG does not Granger Cause Metal	1.09008	0.33664
Oil & Gas does not Granger Cause FMCG	2.77275	0.06303
FMCG does not Granger Cause Oil & Gas	2.25700	0.10526
PSU does not Granger Cause FMCG	1.85748	0.15667
FMCG does not Granger Cause PSU	1.15836	0.31447
IT does not Granger Cause Healthcare	3.10859	0.04515*
Healthcare does not Granger Cause IT	2.72040	0.06639
Metal does not Granger Cause Healthcare	4.60702	0.01022*
Healthcare does not Granger Cause Metal	1.16818	0.31141
Oil & Gas does not Granger Cause Healthcare	3.85071	0.02162*
Healthcare does not Granger Cause Oil & Gas	1.95352	0.14238
PSU does not Granger Cause Healthcare	2.95321	0.05268
Healthcare does not Granger Cause PSU	2.13193	0.11921
Metal does not Granger Cause IT	1.64752	0.19311
IT does not Granger Cause Metal	3.16330	0.04276*
Oil & Gas does not Granger Cause IT	0.70830	0.49276
IT does not Granger Cause Oil & Gas	2.85338	0.05817
PSU does not Granger Cause IT	1.16146	0.31350
IT does not Granger Cause PSU	4.70332	0.00929*
Oil & Gas does not Granger Cause Metal	2.49708	0.08290

Metal does not Granger Cause Oil & Gas	0.55113	0.57649
PSU does not Granger Cause Metal	0.06297	0.93897
Metal does not Granger Cause PSU	9.65736	7.1E-05*
PSU does not Granger Cause Oil & Gas	5.28844	0.00521
Oil & Gas does not Granger Cause PSU		

Granger Causality Test statistics as reported in the table are obtained by running the following bi-variate regressions:

$$x_t = \sum_{i=1}^{p} \alpha_i x_{t-1} + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_t \qquad \text{......... (5)}$$

$$y_t = \sum_{i=1}^{p} \alpha_i y_{t-1} + \sum_{i=1}^{p} \beta_i x_{t-i} + \varepsilon_t \qquad \text{.......... (6)}$$

where x_t (y_t) is assumed to be a function of past values of itself and past and contemporaneous values of y_t (x_t) and where x_t and y_t represent return series. The asterisk (*) indicates that the null hypothesis that one sector does Granger cause the other sectors is rejected at 5% level of significance.

Table - V

Estimated coefficient for variance-covariance equations

Pair	Garch Coefficients	Value	Std. Error	t value	Pr (> t)	Multivariate L-J Box stat.
Auto & Bank	h_{11}	0.9360476	0.0230929	40.534	0.0000	35.47 (0.909)
	h_{21}	-0.0565496	0.0257639	-2.195	2.843e-002	

		h_{12}	-0.0396228	0.0131052	-3.023	2.571e-003	
		h_{22}	0.9471633	0.0156986	60.334	0.000	
Auto & capital		h_{11}	0.871670	0.0622126	14.0112	0.000e+000	57.6529 (0.1604)
		h_{21}	-0.016664	0.0770651	-0.2162	8.289e-001	
		h_{12}	0.025307	0.0452991	0.5587	5.765e-001	
		h_{22}	0.872016	0.0526113	16.5747	0.000e+000	
Auto & consumer		h_{11}	0.952742	0.0277080	34.3851	0.000e+000	38.1465 (0.8449)
		h_{21}	0.023584	0.0523729	0.4503	6.526e-001	
		h_{12}	-0.041295	0.0349527	-1.1815	2.377e-001	
		h_{22}	0.794668	0.0527876	15.0541	0.000e+000	
Auto & FMCG		h_{11}	0.751046	0.3356941	2.2373	2.551e-002	60.1498 (0.1121)
		h_{21}	0.306358	0.4109323	0.7455	4.562e-001	
		h_{12}	0.137038	0.3659787	0.3744	7.082e-001	
		h_{22}	0.509357	0.4321708	1.1786	2.389e-001	
Auto & Healthcare		h_{11}	0.938663	0.0332010	28.2721	0.000e+000	42.0750 (0.7132)
		h_{21}	0.022423	0.0410756	0.5459	5.853e-001	
		h_{12}	-0.020585	0.0566992	-0.3631	7.166e-001	
		h_{22}	0.798129	0.0614230	12.9940	0.000e+000	
Auto & IT		h_{11}	0.913748	0.0188747	48.4112	0.000e+000	53.2285 (0.2800)
		h_{21}	-0.080599	0.0226438	-3.5594	3.912e-004	
		h_{12}	-0.016250	0.0173830	-0.9348	3.501e-001	
		h_{22}	0.939360	0.0203233	46.2209	0.000e+000	
Auto & Metal		h_{11}	0.8709367	0.0473315	18.400765	0.000e+000	53.5881 (0.2686)
		h_{21}	-0.1380878	0.0614092	-2.248650	2.478e-002	
		h_{12}	0.0410018	0.0302392	1.355914	1.755e-001	

	h_{22}	1.0104800	0.0341704	29.571752	0.000e+000	
						42.6250 (0.6921)
Auto & Oil & Gas	h_{11}	0.997497	0.0180610	55.229	0.000e+000	
	h_{21}	0.027970	0.0243461	1.149	2.509e-001	
	h_{12}	-0.063080	0.0108785	-5.799	9.269e-009	
	h_{22}	0.903817	0.0152925	59.102	0.000e+000	
Auto & PSU						41.8167 (0.7229)
	h_{11}	0.88011893	0.0342539	25.6939559	0.000e+000	
	h_{21}	-0.10217314	0.0354484	-2.8823044	4.042e-003	
	h_{12}	0.02218743	0.0217260	1.0212399	3.074e-001	
	h_{22}	0.99726484	0.0222246	44.8721229	0.000e+000	
						47.3962 (0.4975)
Bank & Capital	h_{11}	0.982105	0.0329904	29.7694	0.000e+000	
	h_{21}	0.032855	0.0508112	0.6466	5.180e-001	
	h_{12}	-0.073631	0.0388912	-1.8932	5.865e-002	
	h_{22}	0.796105	0.0524809	15.1694	0.000e+000	
Bank & consumer						40.3069 (0.7771)
	h_{11}	0.978085	0.0130138	75.1576	0.000e+000	
	h_{21}	-0.005759	0.0218519	-0.2636	7.922e-001	
	h_{12}	-0.067865	0.0213283	-3.1819	1.513e-003	
	h_{22}	0.837873	0.0318117	26.3385	0.000e+000	
Bank & FMCG						60.1774 (0.1117)
	h_{11}	0.983985	0.0121981	80.66694	0.000e+000	
	h_{21}	-0.005213	0.0159298	-0.32724	7.436e-001	
	h_{12}	-0.097755	0.0257475	-3.79667	1.565e-004	
Bank & Healthcare	h_{22}	0.839804	0.0304442	27.58501	0.000e+000	
						29.5112 (0.9836)
	h_{11}	0.9764390	0.0206406	47.30679	0.000e+000	
	h_{21}	0.0004485	0.0238761	0.01878	9.850e-001	
	h_{12}	-0.0970137	0.0452871	-2.14219	3.245e-002	
Bank & IT	h_{22}	0.8152936	0.0439662	18.54365	0.000e+000	
						44.5905

						(0.6133)
	h_{11}	0.9587415	0.0129923	73.7928	0.000e+000	
	h_{21}	-0.0369206	0.0142548	-2.5901	9.752e-003	
	h_{12}	-0.0808230	0.0204537	-3.9515	8.378e-005	
Bank & Metal	h_{22}	0.8927913	0.0205458	43.4537	0.000e+000	
						48.7727 (0.4418)
	h_{11}	9.400e-001	0.0175412	5.359e+001	0.000e+000	
	h_{21}	-5.524e-002	0.0221646	-2.492e+000	1.288e-002	
	h_{12}	-5.688e-003	0.0109847	-5.178e-001	6.047e-001	
	h_{22}	9.668e-001	0.0135866	7.116e+001	0.000e+000	
Bank & Oil & Gas						62.7116 (0.0753)
	h_{11}	0.947493	0.0198122	47.8236	0.000e+000	
	h_{21}	-0.035918	0.0201595	-1.7817	7.514e-002	
	h_{12}	0.012893	0.0212167	0.6077	5.436e-001	
Bank & PSU	h_{22}	0.960953	0.0202959	47.3472	0.000e+000	
						83.2554 (0.0012)
	h_{11}	9.212e-001	0.0251415	3.664e+001	0.000e+000	
	h_{21}	-5.721e-002	0.0213606	-2.678+000	7.532-003	
	h_{12}	-6.295e-003	0.0195727	-3.216e-001	7.478e-001	
Capital & consumer	h_{22}	9.685e-001	0.0175318	5.524e+001	0.000e+000	
						54.6088 (0.2379)
	h_{11}	0.8463517	0.0330563	25.6033	0.000e+000	
	h_{21}	0.0512855	0.0464028	1.1052	2.694e-001	
Capital & FMCG	h_{12}	0.0438262	0.0383646	1.1424	2.536e-001	
	h_{22}	0.7699626	0.0556898	13.8259	0.000e+000	73.9369 (0.0095)
	h_{11}	0.887500	0.338912	26.1867	0.000e+000	
	h_{21}	0.043187	0.0285130	1.5146	1.302e-001	
	h_{12}	-0.040455	0.0412646	-0.9804	3.2727e-001	
Capital & Healthcare	h_{22}	0.868683	0.0311989	27.8434	0.000e+000	58.2571 (0.1475)

Capital & IT		h_{11}	0.897922	0.0409523	21.9260	0.000e+000	
		h_{21}	0.068761	0.0447959	1.5350	1.251e-001	
		h_{12}	-0.065304	0.0804906	-0.8113	4.174e-001	
		h_{22}	0.660418	0.0813506	8.1182	1.554e-015	46.0878 (0.5515)
Capital & Metal		h_{11}	0.8719631	0.0197673	44.1114	0.000e+000	
		h_{21}	-0.0857385	0.0172512	-4.9700	8.022e-007	
		h_{12}	-0.0547268	0.0226171	-2.4197	1.573e-002	
		h_{22}	0.9441862	0.0179510	52.5979	0.000e+000	56.6929 (0.1825)
Capital & Oil & Gas		h_{11}	8.162e-001	0.0325576	2.507e+001	0.000e+000	
		h_{21}	-1.124e-001	0.0280457	-4.007e+000	6.657e-005	
		h_{12}	4.939e-002	0.0217242	2.274e+000	2.323e-002	76.8517 (0.0051)
		h_{22}	1.002e+000	0.0172841	5.798e+001	0.000e+000	
Capital & PSU		h_{11}	0.860918	0.0263878	32.626	0.000e+000	
		h_{21}	-0.031442	0.0224310	-1.402	1.613e-001	
		h_{12}	0.027711	0.0223355	1.241	2.151e-001	74.4989 (0.0084)
		h_{22}	0.955609	0.0185199	51.599	0.000e+000	
		h_{11}	0.8215161	0.0329959	24.8975	0.000e+000	
		h_{21}	-0.0954858	0.0236681	-4.0344	5.942e-005	
		h_{12}	0.0564756	0.0286464	1.9715	4.898e-002	
Consumer & FMCG		h_{22}	1.0049411	0.0200782	50.0513	0.000e+000	
							50.6075 (0.3710)
Consumer & Healthcare		h_{11}	0.7305050	0.0767757	9.5148	0.000e+000	
		h_{21}	-0.0103453	0.0473323	-0.2186	8.270e-001	
		h_{12}	0.1214745	0.0771125	1.5753	1.155e-001	59.2279 (0.1284)

		h_{22}	0.9267326	0.0460800	20.1114	0.000e+000	
Consumer & IT		h_{11}	0.8498496	0.0693306	12.25794	0.000e+000	33.6931 (0.9415)
		h_{21}	0.0191772	0.0506208	0.37884	7.049e-001	
		h_{12}	0.0030587	0.0998727	0.03063	9.756e-001	
		h_{22}	0.8064436	0.0718034	11.23127	0.000e+000	
Consumer & Metal		h_{11}	0.7907305	0.0512897	15.4170	0.000e+000	42.8771 (0.6822)
		h_{21}	0.0369090	0.0373345	0.9886	3.231e-001	
		h_{12}	0.0153127	0.0448062	0.3418	7.326e-001	
		h_{22}	0.8843566	0.0342776	25.7798	0.000e+000	
Consumer & Oil & Gas		h_{11}	0.82653550	0.0520590	15.8768850	0.000e+000	48.5242 (0.4517)
		h_{21}	-0.11411577	0.0465969	-2.4489971	1.452e-002	
		h_{12}	0.05704321	0.0344948	1.6536741	9.854e-002	
		h_{22}	1.00310727	0.0289090	34.6988022	0.000e+000	
Consumer & PSU		h_{11}	7.404e-001	0.0544890	1.359e+001	0.0000000	29.2382 (0.9851)
		h_{21}	-9.349e-002	0.0301467	-3.101e+000	0.0019886	
		h_{12}	9.958e-002	0.0389293	2.558e+000	0.0106902	
		h_{22}	1.001e+000	0.0217197	4.609e+001	0.0000000	
FMCG & Healthcare		h_{11}	0.7698482	0.0544732	14.1326102	0.000e+000	54.3944 (0.2441)
		h_{21}	-0.1047117	0.0318572	-3.2869048	1.052e-003	
		h_{12}	0.0801619	0.0443992	1.8054792	7.134e-002	
		h_{22}	1.0053295	0.0246978	40.7052567	0.000e+000	
FMCG & IT		h_{11}	0.9527524	0.0803390	11.85916	0.000e+000	33.6564 (0.9420)
		h_{21}	0.0842646	0.1008882	0.83523	4.038e-001	
		h_{12}	-0.0810467	0.1143531	-0.70874	4.787e-001	
		h_{22}	0.6895032	0.1400404	4.92360	1.012e-006	

FMCG & Metal	h_{11}	0.8782078	0.0207942	42.2334	0.000e+000	66.2935 (0.0411)
	h_{21}	-0.1035091	0.0217220	-4.7652	2.201e-006	
	h_{12}	-0.0260462	0.0140886	-1.8487	6.482e-002	
	h_{22}	0.9603100	0.0130388	73.6540	0.000e+000	
FMCG & Oil & Gas	h_{11}	0.892118	0.0506616	17.6094	0.000e+000	48.0443 (0.4711)
	h_{21}	-0.010119	0.0575425	-0.1759	8.604e-001	
	h_{12}	0.028836	0.0277798	1.0380	2.995e-001	
	h_{22}	0.945674	0.0319471	29.6013	0.000e+000	
FMCG & PSU	h_{11}	0.889165	0.0322807	27.5448	0.000e+000	44.9847 (0.5971)
	h_{21}	-0.067470	0.0297635	-2.2669	2.364e-002	
	h_{12}	-0.006362	0.0174347	-0.3649	7.153e-001	
	h_{22}	0.969606	0.0167665	57.8300	0.000e+000	
Healthcare & IT	h_{11}	0.82125550	0.0406717	20.192328	0.000e+000	47.5395 (0.4916)
	h_{21}	-0.11439521	0.0323349	-3.537823	4.242e-004	
	h_{12}	0.01476076	0.0209699	0.703903	4.817e-001	
	h_{22}	0.98646377	0.0164017	60.143995	0.000e+000	
Healthcare & Metal	h_{11}	0.875083	0.0275565	31.756	0.000e+000	70.5142 (0.0188)
	h_{21}	-0.058064	0.0283983	-2.045	4.118e-002	
	h_{12}	-0.072115	0.0179361	-4.021	6.293e-005	
	h_{22}	0.904807	0.0168986	53.543	0.000e+000	
Healthcare & Oil & Gas	h_{11}	6.883e-001	0.0782523	8.795e+000	0.000e+000	43.7443 (0.6478)
	h_{21}	-1.742e-001	0.0890219	-1.956e+000	5.073e-002	
	h_{12}	9.840e-002	0.0346137	2.843e+000	4.575e-003	
	h_{22}	1.019e+000	0.0358552	2.841e+001	0.000e+000	
Healthcare						51.6433

& PSU	h_{11}	0.815828	0.0400462	20.372	0.000e+000	(0.3334)
	h_{21}	-0.136974	0.0408142	-3.356	8.240e-004	
	h_{12}	0.008696	0.0208528	0.417	6.768e-001	
	h_{22}	0.974815	0.0210704	46.265	0.000e+000	
IT & Metal	h_{11}	0.76734837	0.0523872	14.6476175	0.000e+000	42.1104 (0.7118)
	h_{21}	-0.19675979	0.0521769	-3.7710144	1.733e-004	
	h_{12}	0.05054107	0.0269943	1.8722885	6.149e-002	
	h_{22}	1.01904263	0.0264541	38.5212113	0.000e+000	
IT & Oil & Gas	h_{11}	0.9277533	0.0180547	51.38576	0.000e+000	48.0154 (0.4722)
	h_{21}	-0.0561203	0.0210896	-2.66104	7.929e-003	
	h_{12}	-0.0083883	0.0079395	-1.05654	2.910e-001	
	h_{22}	0.9688513	0.0091272	106.15001	0.000e+000	
IT & PSU	h_{11}	0.8799130	0.0214910	40.9433	0.000e+000	45.0880 (0.5929)
	h_{21}	-0.0810786	0.0230301	-3.5205	4.524e-004	
	h_{12}	-0.0049059	0.0100321	-0.4890	6.249e-001	
	h_{22}	0.9640730	0.0114249	84.3835	0.000e+000	
Metal & Oil & Gas	h_{11}	0.88095599	0.0211781	4.160e+001	0.000e+000	83.7592 (0.0011)
	h_{21}	-0.07632949	0.0178714	-4.271e+000	2.154e-005	
	h_{12}	-0.01545728	0.0099059	-1.560e+000	1.190e-001	
	h_{22}	0.96920868	0.0077823	1.245e+002	0.000e+000	
Metal & PSU	h_{11}	1.017804	0.0215177	47.30084	0.000e+000	56.3616 (0.1906)
	h_{21}	0.049450	0.0206672	2.39266	1.693e-002	
	h_{12}	-0.104587	0.0284322	-3.67848	2.486e-004	
	h_{22}	0.870697	0.0253820	34.30375	0.000e+000	
Oil & Gas & PSU	h_{11}	0.9488423	0.0188057	50.45499	0.000e+000	49.4997 (0.4132)

	h_{21}	-0.0280019	0.0138279	-2.02503	4.316e-002	
	h_{12}	-0.0316333	0.0238633	-1.32561	1.853e-001	
	h_{22}	0.9642771	0.0173961	55.43055	0.000e+000	
	h_{11}	0.906152	0.0234179	38.6949	0.000e+000	
	h_{21}	-0.056936	0.0220508	-2.5820	9.980e-003	
	h_{12}	0.024887	0.0254568	0.9776	3.285e-001	
	h_{22}	0.988773	0.0231497	42.7121	0.000e+000	

The estimated coefficients reported in the table are obtained by running the following variance-covarience equations of the bivariate BEKK model:

$$\begin{bmatrix} H_{11,t} & H_{12,t} \\ H_{21,t} & H_{22,t} \end{bmatrix} = C'C + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} H_{11,t-1} & H_{12,t-1} \\ H_{21,t-1} & H_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \qquad \text{....(10)}$$

where c_{ij} are elements of a 2 x 2 symmetric matrix of constants C, the elements a_{ij} of the symmetric 2 x 2 matrix A_i measure the degree of innovation from index *i* to index *j*.