Article

Shock and Volatility Spillovers Among Equity Sectors of the National Stock Exchange in India

Global Business Review
19(1) 227–240

SAGE Publications
sagepub.in/home.nav
DOI: 10.1177/0972150917713290
http://gbr.sagepub.com

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Abstract

The basic thrust of this article is to examine how shocks and volatility are transmitted across sector indices. This article employs the autoregressive asymmetric BEKK-GARCH model. The study is based on daily data from the National Stock Exchange (NSE) of India from January 2004 to January 2014. Volatility spillover was found to be bidirectional among the two pro-cyclical sectors: Finance and IT. But, there was a unidirectional shock and volatility spillover from the non-cyclical FMCG sector to both the pro-cyclical sectors. The FMCG sector has remained almost unaffected by the spillover from the other sectors. Moreover, the evidence of asymmetric spillover has been found to be present in most of the case. Second, correlations between the sectors were found to be higher during the period of global financial crisis. But no such evidence was found in the context of the Euro zone debt crisis. Understanding the dynamics of shocks and volatility transmission is necessary for risk management in general and for optimal portfolio allocation and hedging strategy in particular. To the best of our knowledge, this is the first study on Indian stock market which has analysed the dynamics of shock and volatility transmission across sector indices.

Keywords

Multivariate GARCH model, sector indices, shock transmission, volatility spillover

Introduction

Global linkages through cross-border financial flows have become more and more important for developing markets in the trail of financial globalization. Due to this rapid pace of financial globalization, equity sector investment in developing countries has become more attractive for investors. Since the last decade, stock markets in the developing countries have grown rapidly in both volume and value, especially for the so-called emerging economies. This has provided the opportunity for earning higher returns.

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But, emerging equity markets are often blamed for being very volatile. Hence, investing in equity markets of the developing countries is always lucrative as well as precarious.

Choosing proper stocks is an art in itself. Following the top-down approach, an investor first chooses the country, then selects the sector and finally picks the individual companies. Plenty of researches have been done on the upper and lower ends. Hamao, Masulis and Ng (1990), King and Wadhwani (1990), King, Sentana and Wadhwani (1994), Lin, Engle and Ito (1994), Karolyi (1995), Soydemir (2000), Diebold and Yilmaz (2009) among many others have studied the transmission mechanism across the markets. Veredas and Luciani (2012) analysed 90 individual firms listed in S&P 100. Koulakiotis, Dasilas and Papasyriopoulos (2009) examined the transmission mechanism between portfolios of cross-listed equities within three European financial regions. Das (2016) has analysed the nexus between the Indian stock market and the other major Asian markets. But the missing link in this literature is the inadequate focus on how information transmission occurs across the sectors. Because of the limited research on sector index, many important questions remain unanswered. For example, how the volatility in one sector affects other? Which sector is prone to be more volatile in response to any unanticipated shocks emanating from other sectors? Is there any interdependence between an aggressive sector and a defensive sector? What is the scope for diversifying portfolio risk?

Since different financial assets are traded based on these sector indexes, it is of paramount importance for financial market participants to understand the shocks and volatility transmission over time and across sectors.[1] In this article, we document a number of stylized facts about the dynamics of shocks and volatility transmission among the three Indian sector indexes, namely the finance, FMCG and IT sectors. The basic thrust of this article is to investigate how shocks and volatility are transmitted across these sector indices.

Several types of research have been done to explore the linkages between Chinese A and B share market. The study includes Fung, Lee and Leung (2000) and Yang (2003), among others. Wang, Kutan and Yang (2005) examined the information flows within and across the sectors of the two Chinese stock exchanges in Shanghai and Shenzhen. Using generalized forecast error variance decomposition, they found strong evidence of interactions between the sectors. Moreover, the finance sector in Shenzhen showed the best diversification potential. Hassan and Malik (2007) also found a strong degree of interdependence among the sector indices in the context of the US economy. The study employed the BEKK model. Using the multivariate VAR-GARCH model, Hammoudeh, Yuan and McAleer (2009) examined the shocks and volatility spillover among the three sectors in Saudi Arabia, Kuwait, Qatar and UAE. Exploiting the vector error correction model, Al-Fayoumi, Khamees and Al-Thuneibat (2009) have explored the dynamic linkages between the four sector indices in the Amman Stock Exchange. However, it is hard to find any study that has explored the shocks and volatility transmission across the sector indices in India.[2]

This article employs the technique of AR (1) asymmetric trivariate BEKK-GARCH model on the daily data from January 2004 to January 2014 to unearth the aforementioned objectives. Our main findings are as follows. Volatility spillover was found to be bidirectional among the two pro-cyclical sectors: finance and IT. But, there was a unidirectional shock and volatility spillover from the non-cyclical FMCG sector to both the pro-cyclical sectors. The FMCG sector has remained almost unaffected by the spillover from the other sectors. Moreover, the evidence of asymmetric spillover has been found to be significant in most of the case. Correlations between the sectors were found to be higher during the period of global financial crisis. But no such evidence was found in the context of the Euro zone debt crisis. The FMCG sector has shown the potential for diversification.

These results have important implications for the market participants. Understanding the dynamics of shocks and volatility transmission is necessary for risk management in general and optimal portfolio allocation and hedging strategy in particular. To be specific, these results can be used to calculate risk minimizing portfolio weights and dynamic hedge ratios. Additionally, the results are useful for building accurate asset pricing models, forecasting volatility in sector returns and our understanding of the equity markets.

The rest of this article is organized as follows. The next section describes the data and the summary statistics. The third section deals with the econometric framework. The following section provides the results and some discussion. And the last section concludes this article.

Data

The data series consists of three sector indices of the National Stock Exchange (NSE) of India, namely S&P CNX Finance (hereafter, Finance), S&P CNX FMCG (hereafter, FMCG) and S&P CNX IT (hereafter, IT). The Finance index is designed to reflect the behaviour of the Indian financial market that includes banks, financial institutions, housing finance and other financial services companies. It consists of 15 stocks that are listed on the NSE. The FMCG index contains 15 stocks from the FMCG sector listed on the NSE. It shows the performance of the FMCG sector in India. The IT index which includes 20 companies listed on the NSE reflects the behaviour of the Indian IT sector. There are 11 sector indices[3] provided by the NSE. Among them, we choose these three indices based on their market representation.[4] Finance, FMCG and IT index, respectively, represent 18.64 per cent, 10.12 per cent and 13.69 per cent of the free-float market capitalization of the stocks listed on the NSE.

The sample covers the data from 1 January 2004 to 31 January 2014. Daily closing data in a total of 2,515 observations were obtained from the NSE. It was a period of mixed blessing for the Indian economy owing to both domestic as well as global factors. Following the global queue, there was a boom in the economy, followed by the global financial crisis and thereafter a quick reversal of the Indian economy, which was further followed by the Euro zone crisis and afterward the domestic macroeconomic headwinds.[5] Within this period, the Indian economy experienced its highest growth rate and stock market peak on the one hand and the global financial crisis followed by the Euro zone crisis on the other hand.

The rate of change in the price series is calculated as continuously compounded returns, or $R_{i,t} = \ln [P_{i,t}/P_{i,t-1}]$, where $R_{i,t}$ denotes the continuously compounded return for index I at time t and $P_{i,t}$ denotes the price level of index i at time t. The return series are shown in Figures A1a–c. The graphs strongly indicate that the return series are stationary. In Table A1, we report the descriptive statistics for daily index returns.

The FMCG sector has lower variance in comparison with the other two sectors, which is consistent with the belief that the FMCG sector is less volatile. All the returns are negatively skewed, which indicates that there is a greater chance that the sectors go down than up in a given time period. All are leptokurtic in nature, implying a fat-tailed distribution. Non-normality is supported by the Jarque–Bera (JB) test statistics that are significant at the 1 per cent level for all index returns. The Ljung–Box (LB) test statistics shows the significant presence of autocorrelation in all the three return series. Moreover, the LB statistics for squared return series are also significant for all. This indicates the time-varying dependency in the second moment of residuals. In other words, it confirms the presence of the ARCH effect. The return series shown in Figures A1a–c clearly points towards the volatility clustering in all the three series. The Phillips–Perron (PP) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests indicate that the series are stationary.

Econometric Model

The univariate ARCH family of models has been extensively used in this literature for modelling volatility in asset markets.[6] In this article, we use the multivariate GARCH (MGARCH) framework. The choice of MGARCH models over the univariate framework is motivated by the following reason. The multivariate framework not only provides an analysis of volatility and the accompanying interlinkages between the assets concerned but it also allows an estimation of the time-varying covariances and correlations. Moreover, the univariate GARCH model needs to be extended in a multivariate framework when we deal with a vector of returns (i.e., portfolio return), instead of a single asset.

In MGARCH models, defining the covariance matrix is of prime importance.[7] There are different specifications of MGARCH models. Broadly speaking, there are three main approaches: (a) Direct generalization of the univariate GARCH model. This includes VECH, BEKK and factors models. (b) Linear combination of univariate GARCH models. Orthogonal and latent factor models fall into this category. (c) Non-linear combination of univariate GARCH models. Conditional correlation models belong to this category. Among them, most popular parameterizations are the VECH, BEKK and dynamic conditional correlation models.

The first MGARCH model for the conditional covariance matrices was the so-called VECH model proposed by Bollerslev, Engle and Wooldridge (1988).

Consider an $N\times 1$ dimensional stochastic vector process $\{Y_t\}$:

$$Y_t = \mu_t + \varepsilon_t,$$

where, μ_t is the conditional mean vector. ε_t is an $N\times 1$ vector of a random process.

$\varepsilon_t | F_{t-1} \sim N(0, H_t)$; F_{t-1} is the information set at time $t-1$; H_t is the $N\times N$ parameter vector.

The VECH specification is presented as

$$\mathrm{Vech}(H_t) = \mathrm{Vech}(C) + \sum\nolimits_{i=1}^{q} A_i \mathrm{Vech}(\varepsilon_{t-i}\varepsilon'_{t-i}) + \sum\nolimits_{j=1}^{p} B_j \mathrm{Vech}(H_{t-j}).$$

Vech(.) is an operator that converts a matrix into a vector. It denotes the operator that stacks the lower triangular portion of an $N\times N$ matrix as a $[N(N+1)/2]\times 1$ vector. H_t is the covariance matrix of the residuals. C is an $[N(N+1)/2]\times 1$ vector. A and B are square matrices of order $[N(N+1)/2]$ and ε is the $N\times 1$ vector.

Although the Vech model is able to capture the volatility spillover effect, it suffers from two major drawbacks: First of all the condition for H_t to be positive definite is not guaranteed. Moreover, for N number of variables, $(p+q)\times(N(N+1)/2)^2+N(N+1)/2$ number of parameters has to be estimated,[8] which is quiet large unless N is not small.[9]

The beauty of the BEKK[10] model lies in the fact that it ensures the H_t matrix to be positive definite. It takes the following form.

$$H_t = C'C + \sum_{j=1}^{q}\sum_{k=1}^{k} A'_{kj}\varepsilon_{t-j}\varepsilon'_{t-j}A_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{k} B'_{kj}H_{t-j}B_{kj},$$

where A_{kj}, B_{kj} and C are $N\times N$ matrices. C is a lower triangular matrix.[11]

The first order BEKK model[12] can be depicted as follows.

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B.$$

The most important feature of the BEKK model is that it is flexible enough to allow the different conditional covariances and variances to influence each other, and at the same time, does not require estimating a large number of parameters.[13]

It is well documented in the existing literature that stock market volatility responds asymmetrically to negative (bad news) and positive (good news) shocks. Usually, it is observed that following a negative shock, volatility tends to increase more than following a positive shock of the same magnitude.[14] The standard BEKK model fails to capture this asymmetric response. In order to overcome this limitation, Kroner and Ng (1998) proposed an asymmetric BEKK model in line with the approach of Glosten, Jagannathan and Runkle (1993) to a multivariate setting.

In this article, we use the following asymmetric BEKK-GARCH (1, 1) model with AR (1) specification for the mean equations:

$$R_{it} = \mu_i + \alpha I + \varepsilon_{it}$$

where, $R_{i,t}$ denotes the return of indeI i for time period t, I is a long-term drift coefficient and ε_{it} is the error term. And the following trivariate BEKK specification has been used:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\tau_{t-1}\tau'_{t-1}D.$$

The individual elements for C, A and B matrices are as follows.

$$C = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} D = \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix}$$

Elements of matrices A and B, respectively, capture the effect of shocks and volatility on conditional variances. On the one hand, the diagonal elements of matrix A represent the effect of own past shock on the conditional volatility. On the other hand, the off-diagonal elements of matrix A, that is, the a_{ij} terms capture the effect of the ith market shock on the jth market volatility. In a similar manner, the diagonal elements of matrix B depict the effect of own past volatility and the off-diagonal elements reflect the volatility spillover from the other markets. Here, τ_t captures the asymmetries. τ_t is defined as ε_t if ε_t is negative, and zero otherwise. The diagonal elements in matrix D capture the response of the own market to its own past negative shocks, while the off-diagonal elements, that is, d_{ij}, measure the effect of marIet i on the negative shocks from the jth market. In other words, this captures the cross-market asymmetric responses.

The aforementioned model is estimated by maximizing the following likelihood function.

$$L(\theta) = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{N}(\ln|H_t| + \varepsilon'_t H_t^{-1}\varepsilon_t),$$

where N denotes the number of observations and θ is the vector of the parameters to be estimated. The BFGS algorithm has been used to find the estimates of the parameters and their standard errors.[15]

Empirical Results

This section contains the estimation result of the trivariate asymmetric BEKK-GARCH (1, 1) model with AR (1) specification for mean equations. Estimation results are presented in Table A2.

The mean equation and the variance–covariance equation have been estimated simultaneously by the maximum likelihood method. Finance, FMCG and IT sectors have been labelled as 1, 2 and 3, respectively. The first row of Table A2 shows the AR coefficient of the mean equations. Statistical significance of $R_{i,t-1}$ (for all i = 1, 2, 3) entails that all three sector returns follow an autoregressive process of order 1.[16]

Next, we focus on the variance–covariance equation. The volatility of all three sector returns was affected by its own past shock and volatility. This is indicated by the significant a_{ij} and b_{ij} coefficients for all $i = j = 1, 2, 3$. Own past volatility has played a greater role than own past shock to influence the present volatility. It is reflected by the fact that $a_{ij} < b_{ij}$ for $i = j = 1, 2, 3$. Turning around the asymmetric coefficient it is found that d_{11}, d_{22} and d_{33} are all positive and significant. This asserts that a bad news of an own market amplifies the volatility to a greater extent than a good news. Thus, we get an evidence of the standard leverage effect, as stated in the existing literature.

Next, we focus on the spillover result. The coefficient a_{ij}s (for all i = 1, 3 and j = 1, 2, 3) are statistically insignificant. This entails that there was no shock spillover from the Finance and IT sectors. In other words, any unanticipated shocks emanating from the Finance and IT sectors failed to affect others. However, there was a unidirectional shock spillover from the FMCG sector to the Finance and IT sectors. The statistical significances of a_{21} and a_{23} confirm this. Volatility spillover is found to be bidirectional between the Finance and the IT sector. Both these sectors have more global exposure and, thus, are influenced by several external factors. There exist some common external factors like exchange rate that influence both. This could be the probable reason behind the observed volatility spillover between the Finance and the IT sectors. But, there was a unidirectional volatility spillover from the FMCG sector to the Finance and IT sectors. This is indicated by the significant b_{21} and b_{23} coefficients. However, it is to be noted that both b_{21} and b_{23} are negative. Looking at the d_{ij}s, we find that almost everywhere there is an evidence of asymmetric cross-market spillover, except for the spillover from the IT sector.

Looking at it differently, the results reveal several pragmatic insights regarding the interaction between the pro-cyclical and the non-cyclical sectors. Although there was a bidirectional volatility spillover among the two pro-cyclical sectors, there was a unidirectional shock and volatility spillover from the non-cyclical FMCG sector to both the pro-cyclical sectors. Thus, being a defensive non-cyclical sector, FMCG remained unaffected by the shock and volatility emanating from either of the two pro-cyclical sectors. Hence, a combination of the pro-cyclical- and non-cyclical-sector equities could be a good bet for diversifying the portfolio risk. This result bears a special importance for the market participants.

Next, we statistically test the asymmetric spillover and cross-market spillover restriction from the aforementioned model. The results are reported in Table A3.

First, we test the hypothesis of the trivariate symmetric model versus the trivariate asymmetric model. The chi-squared statistics shows that the null hypothesis of $d_{ij} = 0$ cannot be accepted. Hence, it supports the evidence of asymmetric spillover. In addition to this, the hypothesis of no cross-market spillovers has been tested. The observed chi-squared statistics signifies the presence of cross-market spillover.

Estimated conditional correlations from the aforementioned BEKK model[17] are depicted in Figures A2a–c. Table A4 shows the average conditional correlation for the different phases of the economy.

We focus broadly on three phases, namely the boom period (from 2004 to 2007), crisis period (from 2008 to January 2009) and post-crisis period (from February 2009 to 2014). It is found that the correlation has increased during the period of global financial crisis. This may be attributed to the fact that the market integration tends to increase at the time of stress due to the contagion effect.[18] However, looking at the period of the Euro zone debt crisis,[19] it is observed that the correlation was smaller. Thus, we get a contrasting implication of the global financial crisis and the Euro zone crisis. The result is obvious due to the fact that the severity of Euro crisis was limited than global financial crisis both in terms of extent and persistence.

To conclude, the earlier discussed analysis reveals that all these sectors were interconnected among themselves in different ways over the four phases. Moreover, it also entails the possibility of cross-market hedging and diversifying the unsystematic risk of a portfolio by means of the sector index. These findings bear special significance for the market participants. In particular, the results could be used to calculate the risk minimizing portfolio weights and the risk minimizing hedge ratios.[20]

Conclusion

The primary focus of this article was on exploring the shocks and volatility spillover among the Finance, FMCG and IT sector indices from 1 January 2004 to 31 January 2014. A trivariate asymmetric BEKK model has been used for this. The result entails that the volatility of each sector was influenced by its own past shock and volatility. Regarding the cross-market spillover, the study finds that there was a bidirectional volatility spillover between the two pro-cyclical sectors, namely the Finance and the IT sectors. But, there was a unidirectional shock and volatility spillover from the FMCG sector to the other two sectors. Thus, shocks and volatility spillover were found to be unidirectional between the non-cyclical and the pro-cyclical sectors. This provided the opportunity for portfolio diversification. Moreover, the shocks spillover were found to be asymmetric for most of the cases, including both own-market and cross-market spillover. Following the contagion effect, correlations between the sectors tend to increase during the period of global financial crisis. But no such evidence was found in the context of the Euro zone debt crisis.

In general, there is a shock and volatility transmission across the sectors. Volatility spillover is usually attributed to cross-market hedging and changes in common information. Dynamics of this transmission channels across the sector indices and is especially important for the investors who hold a portfolio consisting of different sector indices as well as for those who focus on a particular sector. The underlying interlinkages across the sectors entail that even if an investor invests in a particular sector, he/she should not only be aware of that particular sector but also of all others. This article has explicitly explained how understanding these dynamics will help them to choose risk minimizing optimal portfolio and cross-market hedge ratio.

Acknowledgement

This article was presented in the 4th IIFT Conference on Empirical Issues in International Trade & Finance, organized by the Indian Institute of Foreign Trade, held in New Delhi (during 18–19 December 2014) and in the Research Scholars' Workshop held in University of Calcutta (during 8–9 July 2014). We are thankful to the participants for helpful comments. We are also grateful to the anonymous referees of the journal for their extremely useful suggestions to improve the quality of this article. However, the usual disclaimers apply.

Appendix

Table A1. Descriptive Statistics for Daily Index Return Over the Sample Period

	Finance	FMCG	IT
Mean	0.00025	0.00030	0.00024
Median	0.00046	0.00047	0.00031
Max	0.07733	0.03606	0.05153
Min	–0.0625	–0.0537	–0.0625
Std. dev	0.00899	0.00609	0.00801
Skewness	–0.0755	–0.4170	–0.1597
Kurtosis	9.04914	8.47937	8.84944
JB	3836.9*	3219.1*	3596.2*
LB(20)	87.68*	35.44**	42.39*
$LB^2(10)$	886.2*	785.5*	656.1*
PP	–43.6*	–48.9*	–49.9*
KPSS	0.035*	0.046*	0.082*
No. of observation	2515	2515	2515

Source: Calculated by the authors.
Note: *(**) represents statistical significance at 1(5)% level of significance.

Table A2. Trivariate Asymmetric BEKK-GARCH Model for the Finance, FMCG and IT Sectors

Coefficient	Finance (i = 1)	FMCG (i = 2)	IT (i = 3)
$R_{i,t-1}$	0.13*	0.07*	0.04*
a_{i1}	0.035**	0.15*	–0.05
a_{i2}	–0.09	0.38*	–0.01
a_{i3}	0.013	0.25*	0.10*
b_{i1}	0.94*	–0.07*	0.06*
b_{i2}	0.008	0.83*	0.013
b_{i3}	0.03**	–0.12*	0.93*
d_{i1}	0.29*	0.15*	–0.06
d_{i2}	0.20*	0.12**	0.01
d_{i3}	0.23*	–0.14**	0.18*

Source: Calculated by the authors.
Note: *(**) represents statistical significance at 1(5)% level of significance.

Table A3. Test for the Restrictions

Hypothesis	Chi-squared Statistics	Degree of Freedom
H_0: D = 0, i.e., no asymmetry	304.226*	9
H_0: $a_{ij} = b_{ij} = d_{ij} = 0$ for $i \neq j$, i.e., no cross-market effect	308.664*	18

Source: Calculated by the authors.
Note: * represents statistical significance at 1% level of significance.

Table A4. Average Conditional Correlation

	Full Sample		Boom (2004–2007)		Crisis (2008–January 2009)		Post-crisis (February 2009–2014)		Euro Zone Crisis (May 2010–December 2012)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
r_{12}	0.52	0.51	0.51	0.49	0.67	0.67	0.49	0.49	0.48	0.46
r_{13}	0.52	0.51	0.50	0.49	0.70	0.72	0.49	0.49	0.48	0.49
r_{23}	0.40	0.38	0.40	0.38	0.58	0.60	0.36	0.35	0.35	0.35

Source: Calculated by the authors.

Table A5. Average Risk Minimizing Portfolio Weights

	Full Sample	Boom (2004–2007)	Crisis (2008–January 2009)	Post-crisis (February 2009–2014)	2013–2014
Finance–FMCG (W_{12})	0.19	0.22	0.03	0.20	0.21
IT–FMCG (W_{32})	0.28	0.30	0.12	0.29	0.38
Finance–IT (W_{13})	0.40	0.43	0.22	0.41	0.38

Source: Calculated by the authors.

Table A6. Average Dynamic Hedge Ratio

	Full Sample	Boom (2004–2007)	Crisis (2008–January 2009)	Post-crisis (February 2009–2014)
Finance–FMCG (h_{12})	0.76	0.71	1.18	0.71
IT–FMCG (h_{32})	0.53	0.51	0.86	0.47
Finance–IT (h_{13})	0.57	0.54	0.84	0.54
FMCG–Finance (h_{21})	0.37	0.39	0.39	0.35
FMCG–IT (h_{23})	0.31	0.32	0.41	0.27
IT–Finance (h_{31})	0.48	0.47	0.59	0.45

Source: Calculated by the authors.

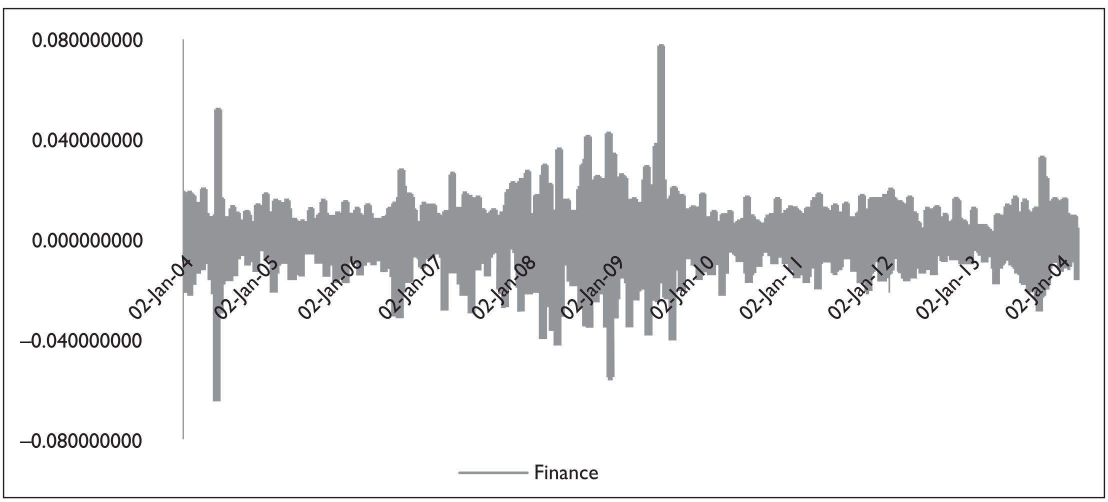

Figure A1a. Daily Return of the Finance Index

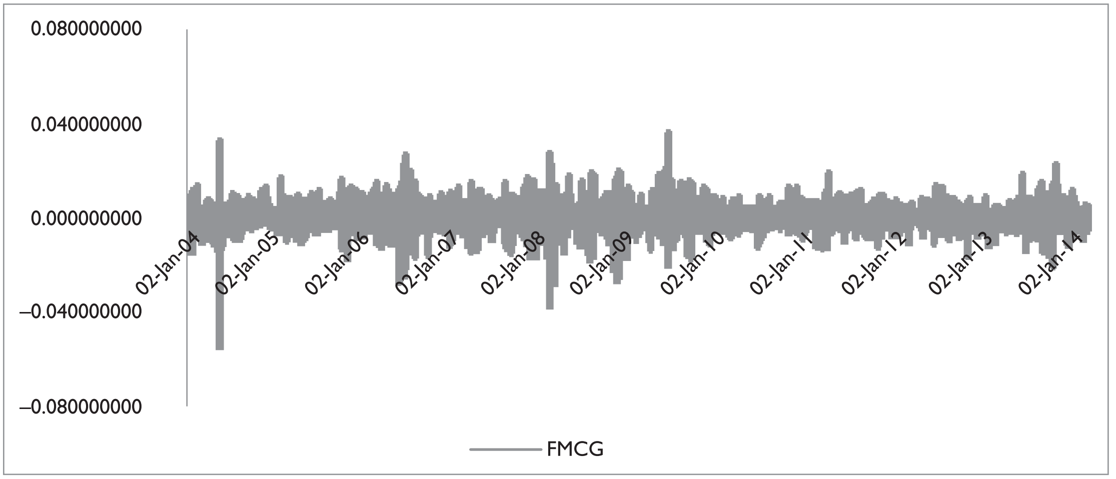

Figure A1b. Daily Return of the FMCG Index

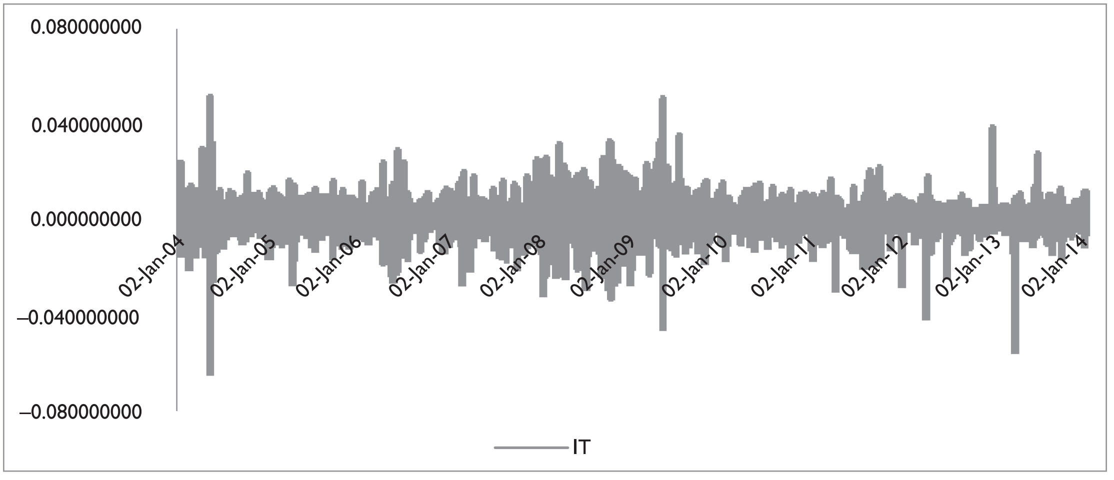

Figure A1c. Daily Return of the IT Index

Source: Authors' own work.

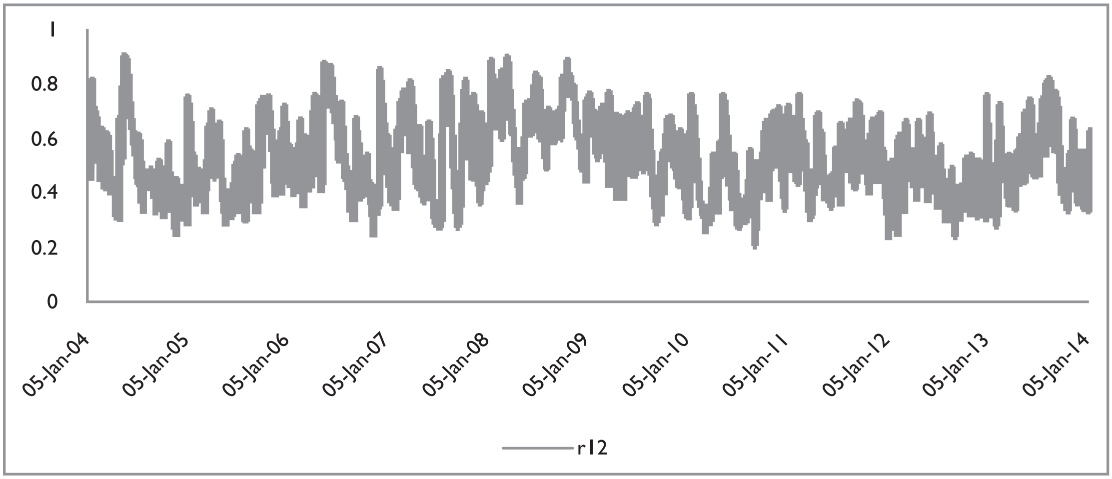

Figure A2a. Conditional Correlation Between the Finance and the FMCG Sectors

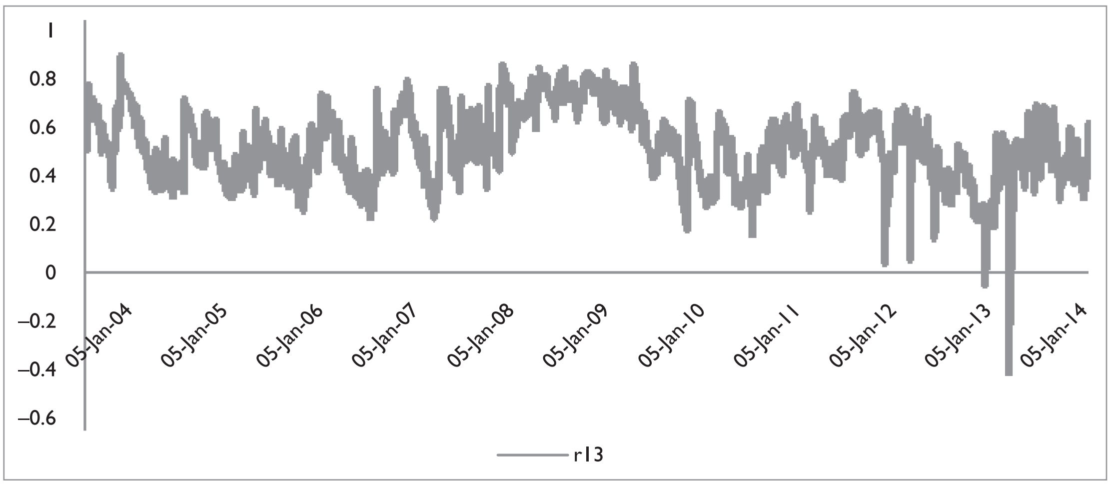

Figure A2b. Conditional Correlation Between the Finance and the IT Sectors

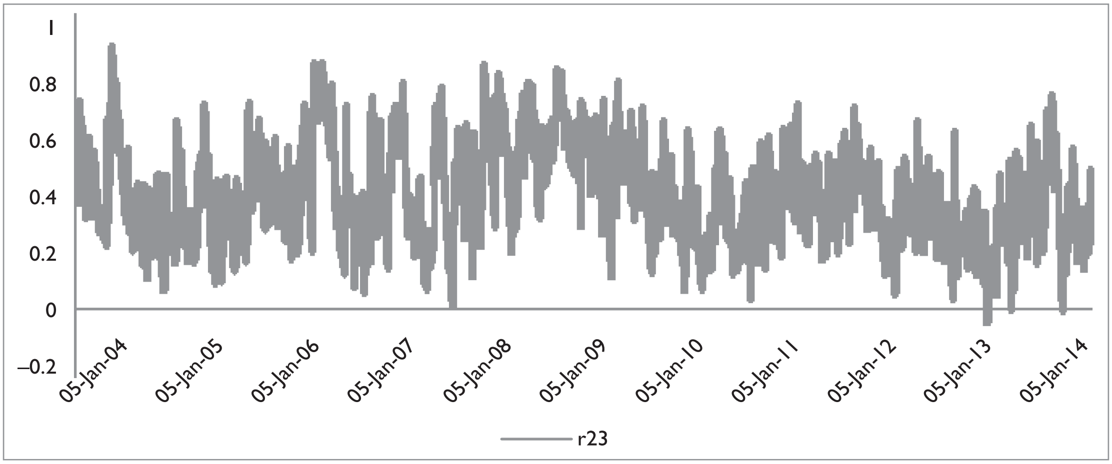

Figure A2c. Conditional Correlation Between the FMCG and the IT Sectors

Source: Authors' own work.

Notes

1. Following Ross (1989) and Chan, Chan and Karolyi (1991) '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'.
2. To the best of our knowledge this is the first study in the Indian context. Karmakar (2010) examined the shocks and volatility transmission between small and large stocks for the Indian economy.
3. Eleven sector indices provided by the NSE are Auto index, Bank index, Energy index, Finance index, FMCG index, IT index, Media index, Metal index, Pharma index, PSU Bank index and Realty index.
4. In order to have a more comprehensive result, it would be always preferable to consider all the 11 sector indices in our analysis. However, this may not be practically tractable. In that case, we have to estimate a huge number of parameters which makes the estimation process unworkable.
5. Sluggish growth, sustained inflation, widening current account deficit and sliding rupee led to the poorest macroeconomic performance.
6. See Bollerslev (2008) for the survey of literature on the ARCH family model.
7. Maintaining a good balance between parsimony and flexibility is much desired for formulating MGARCH specifications. Moreover, the model must ensure that the covariance matrix is positive definite.
8. Even for a trivariate model we have to estimate 78 parameters, which are computationally demanding.
9. In order to overcome this problem of overparameterization, Bollerslev proposed a restrictive version of this model—known as the DVECH (diagonal Vech) model. As the name suggests, it assumes the Ai and Bj matrices to be diagonal matrices. This restriction reduces the number of parameters to $(p+q+1)N(N+1)/2$ (e.g., for $N = 3$, it is equal to 18). Moreover, it also ensures H_t to be positive definite for all values of t. But this model does not permit any interaction between different conditional covariances and variances. In other words, this specification does not allow volatility spillover.
10. The BEKK model is named after Baba, Engle, Kraft and Kroner (1990), who wrote the preliminary version of Engle and Kroner (1995).
11. The purpose of decomposing the constant term into a product of two triangular matrices is to guarantee the positive semi-definiteness of H_t.
12. The first-order BEKK-GARCH model implies $K = 1$, $p = 1$ and $q = 1$.
13. For a bivariate BEKK-GARCH (1, 1) model, only 11 parameters have to be estimated in contrast to 21 parameters in the VECH model.

14. This is referred to as the 'leverage effect', as proposed by Black (1976). The intuition is based on the balance sheet effect which entails that decreasing return tends to deteriorate the debt–equity ratio and, hence, the probability of default magnifies.
15. We have used the RATS Version 8 for the estimation purpose.
16. We also tried AR (2) and AR (3) specifications for a mean model. But they did not improve the estimation results.
17. Generally, it is argued that the BEKK model is used to estimate the conditional covariance and the DCC model is used for conditional correlation. But, the conditional correlation (conditional covariance) can be easily estimated from the BEKK (DCC) model. Moreover, the conditional correlation derived from the BEKK model is consistent for the true conditional correlation. See Caporin and McAleer (2012) for more detailed discussion.
18. Although there is no unique definition of the term 'financial contagion', it is usually defined as a significant increase in cross-market co-movements after a shock to one market or country beyond what would be justified by fundamentals.
19. The problem in Greece outbroke in early 2010. But, we choose 2 May 2010 as a starting date for the Euro zone crisis because on that day the Euro zone members and the IMF agreed on 110 billion bailout package to rescue Greece.
20. Suppose a portfolio consists of two equity sector indices in the same market, then we can use the following formula to calculate the risk minimizing portfolio weights:

$$w_{12,t} = \frac{h_{22,t} - h_{12,t}}{h_{11,t} + h_{22,t} - 2h_{12,t}}$$

and

$$w_{12,t} = \begin{cases} 0, \text{ if } w_{12,t} < 0 \\ w_{12,t}, \text{ if } 0 \leq w_{12,t} \leq 1 \\ 1, \text{ if } w_{12,t} > 1 \end{cases}.$$

Here, $w_{12,t}$ is the portfolio weight for the first sector with respect to the second sector in ₹1 portfolio at time *t*. $h_{11,t}$ and $h_{22,t}$ are the conditional variances of the first and the second sectors, respectively, at time *t*. $h_{12,t}$ is the conditional covariance between sectors 1 and 2 at time *t*. We have calculated both the portfolio weights and the hedge ratios in Table A5 and A6 (appendix) respectively.

The minimum variance hedge ratio or optimal hedge ratio is the ratio of futures position relative to the spot position that minimizes the variance of the portfolio. In order to minimize the risk, a long position of ₹1 taken in one sector index should be hedged by a short position of ₹h_t in another sector index in the same market at time *t*. The h_t is given by

$$h_t = \frac{h_{12,t}}{h_{22,t}}.$$

We have calculated both the portfolio weights and the hedge ratios. The values are given in the appendix.

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