GARCH - BEKK Approach to Volatility Behavior and Spillover : Evidence from India, China, Hong Kong, and Japan

*** Ashish Kumar**
*** Swati Khanna**

Abstract

The present study investigated the volatility behavior and its spillover in stock markets of four Asian countries namely : India, China, Hong Kong, and Japan. ARCH, GARCH (1, 1), and bivariate GARCH - BEKK model was applied to examine and explore the volatility behavior and its spillover from one country to another. The results of the study indicated that the Chinese market suffered the greatest fluctuation and the Indian financial market was the most stable market amongst the chosen markets. A strong regional economic integration and analogous growth pattern was observed between Hong Kong and India. The results further hinted that previous volatility had more impact on the current volatility in comparison to the shocks or news coming to the markets as GARCH coefficient was found to be much larger than ARCH coefficient for each of the markets. The stock market of China was less sensitive to its past shocks ; whereas, the stock market of Japan was the most sensitive to its own past shocks. The GARCH coefficient was highest for China. Therefore, it may be concluded that volatility was more persistent in Chinese markets. According to GARCH - BEKK, information was shared swiftly between stock markets of all the countries, however, with a varied degree. The cross market ARCH effect was strongest between China and Japan followed by Hong Kong and Japan, and it was weakest for China and India. Persistency of cross market volatility was highest for the pair of China and India followed by Hong Kong and India, and lowest for China and Japan.

Key words : volatility, volatility spillovers, GARCH-BEKK models, ARCH effect, GARCH effect

JEL Classification : C58, C49, F65, F63

Paper Submission Date : September 5, 2017 ; Paper sent back for Revision : March 3, 2018 ; Paper Acceptance Date : March 22, 2018

Earth's largest and most populous continent is Asia. It stretches from Afghanistan in the West to the Korean peninsula in the East. The Earth's total surface area of 8.8% is covered by Asia. This crescent shaped continent is marked with extremely diverse climates and geographical features. It comprises of several diverse, divergent, discernible sub - regions and countries. An extreme form of diversity is a universal feature of Asia. Development of the Asian financial markets in the last few decades is characterized by a prologue of policies, which encourages countries to engage in various bilateral & multilateral trade, investments, and economic cooperation. A different set of opportunities have emerged for investors under the present liberalized policy framework. Elimination of investment barriers in equity markets not only increases investment opportunities and returns, but also causes integration of various capital markets. Globalization and liberalization of the economies has increased the speed at which information transcends from one country to another resulting in

* *Assistant Professor,* Guru Gobind Singh Indraprastha University, Sector 16C, Dwarka, Delhi - 110 078.
E-mail : ashish_prl@yahoo.com
** *Research Scholar,* Guru Gobind Singh Indraprastha University, New Delhi & ***Assistant Professor*, Northern India Engineering College, FC -26, Shastri Park, New Delhi - 110 051. E-mail : ganotra_swati@rediffmail.com

speedy integration of the economies and rapid spillover of volatility [1] (Dungey & Martin, 2007 ; Errunza & Losq, 1985; Jorion & Schwartz, 1986; Khuong Nguyen & Bellalah, 2008) across the globe.

Analysis of financial assets' volatility is imperative to academicians, policy makers, and financial market participants for numerous reasons. Firstly, it initiates rational portfolio risk management decisions. Secondly, it is a measure of risk exposure of investments. Thirdly, volatility affects pricing of derivative securities and lastly, volatility is vital in order to calculate the value at risk of a portfolio selection. Hence, volatility is a barometer for the vulnerability of financial market. Volatility is known by its two well-known features. Firstly, it responds asymmetrically to bad and good news and secondly, there is existence of volatility spillovers between different financial markets and asset categories. Volatility spillover shows that a volatility of a time series is affected by its own lags and volatility entering from other markets as well.

Volatility spillover is a common phenomenon in financial markets all around the world. Narula (2016), Rao (2008), and Shamiri and Isa (2010) examined the spillover effect in BRIC nations, Middle East emerging equity markets, and in Asia-Pacific markets, respectively and concluded it as an important aspect of volatility in all financial markets. Volatility spillover has another important feature, which states that financial crisis in international markets also affects the direction and intensity of its spillover (Liu, 2016). The financial crisis of 2007-2009 had its genesis in United States (U.S.), but it transmitted shocks to all major markets across the world. The impact of shocks from U.S. markets always affects the market returns in UK, Hong Kong, and Japan, but this impact of shocks from the U.S. markets was even stronger during the post-crisis era (Liu, 2016).

This study is aimed at investigating the volatility spillover among the four Asian countries, that is, India, China, Hong Kong, and Japan for a period of 7 years by taking the daily closing data of the benchmark indices of the respective nations. Indices considered for the study are Sensex for India, Shanghai Composite Index for China, Nikkei for Japan, and Hang Seng for Hong Kong. The symmetric GARCH BEKK model is used to study the volatility spillover effect. The purpose of using this model is to examine the volatility spillover effect in the post - recession era.

The present study is unique in numerous aspects and contributes to the literature of a diverse mix of Asian countries. It is one of the limited studies exploring the mean and volatility spillover effects in the Asian region. Most of the studies in literature focus on developed countries of U.S., UK, Europe, and Asia. The multivariate GARCH model has been used extensively for analysis. In this study, we have used the GARCH BEKK model for analysis. Furthermore, the study has practical implications for investors, academicians, researchers, and policy makers as the results of our study will help them not only in understanding the behavior of volatility in the selected countries, but also be useful in framing an investment strategy.

Literature Review

Over the years, the studies in the area of volatility spillovers have emerged from different parts of the world, though most of the initial studies in the area have studied the nature of volatility spillover in context of developed nations and other emerging countries in U.S. and Europe (Baele, 2005 ; Wang & Wang, 2010) and the number of studies measuring volatility spillover in emerging economies in Asia are still not many (Johansson & Ljungwall, 2009 ; Tuan, Hwa, Chua, & Lean, 2015 ; Zhou, Zhang, & Zhang, 2012) and there is a wide research gap which needs to be filled.

[1] The spillover effect is a major transmission effect which is of two types - the first effect in which previous return of a market influences market return of itself or other markets is called mean spillover effect and the second one in which previous volatility influences return volatility of itself or other markets is called volatility spillover effect.

Some of the important and influential studies in the area identified include inter - alia (Ahmad & Rana, 2012 ; Bauwens, Laurent, & Rombouts, 2006 ; Campbell & Hamao, 1992 ; Hamao, Masulis, & Ng, 1990 ; Joshi, 2011 ; Liu & Pan, 1997 ; Liu, 2016 ; Nakatani & Teräsvirta, 2009 ; Ng, 2000 ; Narula, 2016 ; Patel, 2017 ; Rittler, 2012 ; Tuan et al., 2015 ; Wei, Liu, Yang, & Chaung, 1995). In the present era of globalization, when interdependence of economies has increased, the results of empirical studies provided in literature appear to be mixed. There are few studies, which have provided evidence that stock markets of different nations are highly correlated and are affected by each other (Bekiros, 2014 ; Kenourgios, 2014). On the other hand, there are studies, which contradict the fact that stock markets are influenced by each other (Bae et al., 2003).

Studies further stated that financial crisis in an economy generally travels to other economies and is an important driver of volatility spillover. It has more effect on emerging markets if it has its genesis in U.S. or any other developed nation (Bekiros, 2014 ; Donadelli, 2015 ; Kenourgios, 2014; Mensi et al., 2013). However, there are few studies (Bordo & Murshid, 2006 ; Beirne et al., 2009) which reported that the U.S. crisis did not have any effect upon the returns of other countries. Volatility also tends to be affected by the macroeconomic variables, for example, growth rate of an economy, inflation, exchange rate, interest rate, and also by the anomalies of the financial markets (Adjasi, 2009 ; Drew et al., 2003 ; Faff & McKenzie, 2007 ; Glosten et al., 1993; Koutmos, 2012 ; Mishra, 2004).

A deeper peep into the literature brings out the information that different types of methodologies such as OLS regression, ARCH/GARCH, and multivariate GARCH models have been used by researchers for studying the nature of volatility in stock market returns of different countries. Researchers like Baumöhl and Lyócsa (2014) ; Hafner and Reznikova (2012) ; Narayan, Sriananthakumar, and Islam (2014) used the DCC (dynamic conditional correlation) model to examine the relationship between time varying correlations and conditional volatility. Symmetric GARCH BEKK model was used by Liu (2016) to study the spillover effect among global financial markets. Bauwens et al. (2006) and Hamao et al. (1990) used the GARCH-M model to study spillover transmissions from one market to the other markets. Several other GARCH family models, that is, E-GARCH, GJR-GARCH, VAR-GARCH have also been suggested by different studies for examining the volatility transmissions amongst different economies (Kumar, 2012 ; Rajan, 2011 ; Singh & Kaur, 2015). Kumar and Kamaiah (2017) used the wavelet model to measure the return and volatility spillover in their study. All these models have their own peculiar strengths and limitations and there is hardly any consensus among the scholars with regard to the choice of a methodology. In this backdrop, the present study is an attempt to overcome the limitations of the previous studies and bridge the literature gap in context of select Asian economies.

Objectives of the Study

(i) To understand the nature of volatility in the sample stock markets.

(ii) To measure the intensity and direction of volatility spillover among the sample stock markets.

Data and Research Methodology

(1) Data : The present study explores the behavior of volatility of select Asian countries. The sample consists of developing and emerging economies of Asia which are India, China, Japan, and Hong Kong. The data considered in the study were collected for a period from April 1, 2008 to October 28, 2016. The data consists of daily market indices of Hang Seng Composite for Hong Kong, Nikkei for Japan, Shanghai Composite Index for China, and Sensex for India.

(2) Research Methodology

(i) Stationarity, Homoscedasticity, and GARCH (1, 1) Models : The closing values of the benchmark indices are usually far from being stationary and also suffer from several other statistical limitations. Therefore, the continuous return for all the benchmark indices have been calculated by using the equation (1) given below. These return variables have been named as Return China, Return Hong Kong, Return India, and Return Japan.

$$R_t = \ln p_t - \ln p_{t-1} \qquad (1)$$

The stationarity of the return series have been tested by applying ADF (Augmented Dickey Fuller Test) unit root test. Further, to analyze the volatility spillovers and integration between chosen economies, the GARCH (p, q) model has been used.

Volatility clustering, which means periods of low volatility are followed by periods of low volatility and periods of high volatility are followed by periods of high volatility, is an essential condition which warrants the use of the GARCH model. Another condition suitable for applying the GARCH model is the presence of ARCH effect or heteroscedasticity in the residuals as presence of heteroscedasticity in the model makes the results of the ordinary least square model more objectionable, which requires the use of a more robust non linear model. For examining the presence of heteroscedasticity, the study has used the Lagrange Multiplier (LM) test. This test has the null hypothesis that the regression model used is homoscedastic and has the following form :

$$y_t = ax_t - u_t \qquad (2)$$

where u_t is the white noise. If the null hypothesis gets rejected, then it is assumed that the error term u_t has an arch effect which means value of u_t^2 $(i < t)$ can be estimated by using its past values.

The variance equation for the GARCH (p, q) model used for the study is as follows :

$$\sigma^2_t = \sigma^2 + \Sigma^p_{i=1} \alpha_i \; u^2_{t-i} + \Sigma^q_{i=1} \beta_i \; \sigma^2_{t-1} \qquad (3)$$

where, σ^2 is unconditional standard deviation, α_i and β_i are the parameters, ε_i is the error term which follows a normal distribution. The GARCH model specifies that its parameters as given in equation above α_i and β_i are non-negative and their sum is less than 1, that is, $\alpha_i \geq 0, \beta_i \geq 0 \; \Sigma^p_{i=1} \alpha_i \leq 1 \; \Sigma^q_{i=1} \beta_i \leq 1$.

The pertinent equations , therefore, for the sample variables can be given as :

$$dChina_t = c + a_2 \, China_{t-1} + U_{1t}$$
$$\sigma^2_{China,t} = \omega + \alpha_1 u^2_{2t-1} + \beta_1 \sigma^2_{China,t-1}$$
$$dHK_t = c + a_1 HK_{t-1} + U_{1t}$$
$$\sigma^2_{HK,t} = \omega + \alpha_1 u^2_{1t-1} + \beta_1 \sigma^2_{HK,t-1}$$
$$dIndia_t = c + a_1 India_{t-1} + U_{1t}$$
$$\sigma^2_{India,t} = \omega + \alpha_1 u^2_{1t-1} + \beta_1 \sigma^2_{India,t-1}$$
$$dJapan_t = c + a_3 Japan_{t-1} + \mathrm{U}_{1t}$$
$$\sigma^2_{Japan,t} = \omega + \alpha_3 u^2_{1t-1} + \beta_1 \sigma^2_{Japan,t-1}$$

(ii) Multivariate GARCH Models : GARCH (1, 1) model with BEKK representation has been applied to explore the extent of volatility spillover in equity markets of India, China, Hong Kong, and Japan. The proposed model is an expansion of Bollerslev (1986) model. The main merit of this model is that it permits an interaction between conditional variances and variances and the BEKK process further helps in studying the volatility transfer. This model is also simple to understand and interpret as it requires fewer numbers of parameters.

For a bivariate GARCH model, the covariance matrix and its BEKK model is as follows :

$$H_{lj,t} = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix}$$

$$H_t = C'C + B'^{H_{t-1}} B + A'\varepsilon'\varepsilon A \qquad (4)$$

$$H_t = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{12} \end{bmatrix} \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{12} \end{bmatrix} + \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{11,t-1} & \varepsilon_{12,t-1} \\ \varepsilon_{21,t-1} & \varepsilon_{22,t-1} \end{bmatrix} H_{t-1} \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} +$$
$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} h_{1,t-1} \\ h_{2,t-2} \end{bmatrix} \begin{bmatrix} h_{1,t-1} \\ h_{2,t-2} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \qquad (5)$$

where, C is the parameter matrix and A, B are ARCH and GARCH coefficient matrices. The BEKK model assumes both ARCH and GARCH coefficients matrices as diagonal matrices. Therefore, all its off diagonal elements are equal to zero.

The log likelihood function of this model can be stated as follows :

$$ln\, l(\theta) = \frac{-pN}{2}\, ln\, 2\pi - \frac{1}{2}\Sigma^{p}_{i=1}(ln|h_t| + \frac{1}{2}\varepsilon_t' H_t \varepsilon_t) \qquad (6)$$

where, N means number of financial markets, P stands for total number of observations, and θ is an unknown parameter.

Data Analysis And Results

(1) Descriptive Statistics : Descriptive statistics of the four return variables are given in the Table 1. From the Table 1, it may be observed that the average returns are positive for India and Japan ; whereas, for the same period, negative returns have been observed in stock markets of China and Hong Kong. The Chinese market has suffered

Table 1. Descriptive Statistics Sample: 1/4/2008 to 28/10/2016

	Return China	Return Hong Kong	Return India	Return Japan
Mean	-0.028537	-0.010947	0.015698	0.008975
Median	0.016947	0.000000	0.052661	0.066183
Maximum	9.034251	16.80068	15.98998	13.23459
Minimum	-8.905770	-13.58202	-11.60444	-12.11102
Std. Deviation	1.884868	1.809718	1.630661	1.787905
Skewness	-0.365532	0.736345	0.351738	-0.421303
Kurtosis	6.827962	15.78080	13.40537	9.839105
Jarque-Bera	1211.856	13206.93	8678.674	3788.776
Probability	**0.000000***	**0.000000***	**0.000000***	**0.000000***
Sum	-54.64783	-18.13742	30.06132	17.18709
Observations	1915	1915	1915	1915

Note : * means significant at the 5% level.

the highest daily loss of -0.028537 and the Indian market has generated the highest daily average return of 0.015698 for the period under study. The highest volatility of 1.884868 has been observed in the stock market of China and lowest volatility of 1.630661 has been reported in the Indian stock market which means that the Chinese stock market is most volatile and the Indian market is the most stable market of the chosen stock markets. The coefficient of skewness is positive for India and Hong Kong ; whereas, Japanese and Chinese markets' returns are negatively skewed. The Jarque - Bera values are larger than the critical value for all the nations, which rejects the null hypothesis that return series are normal. From the kurtosis statistic, it can be concluded that all stock markets are leptokurtic (measure of kurtosis being more than 3).

(2) Correlation Analysis : For the study period, correlation between India and Hong Kong is the highest (0.638141) (see Table 2) which suggests strong regional economic integration in Hong Kong and India and similar growth patterns in the two stock markets. The second highest correlation (0.632465) is observed between Japan and Hong Kong and coefficient of correlation is lowest between India and China (0.291662) for the period of the study. However, this is not negative. From here, it may be inferred that all chosen stock markets are positively related. Hence, they are likely to move in the same direction.

Table 2. Correlation Period - 1/4/2008 to 28/10/2016

	Return China	Return Hong Kong	Return India	Return Japan
Return China	1.000000			
Return Hong Kong	0.506430	1.000000		
Return India	0.291662	0.638141	1.000000	
Return Japan	0.296054	0.632465	0.442405	1.000000

(3) Unit Root Tests : To ensure the stationarity of the data, the results of unit root test need to be checked. According to the Augmented Dickey-Fuller Test, all the return variables are found to be stationary at level (see Table 3).

Table 3. Results of Unit Root Test in the Post-Crisis Era Sample: 1/4/2008 to 28/10/2016

Variables	ADF *p* - value	Stationarity
Return China	0.0000*	Stationary
Return Hong Kong	0.0001*	Stationary
Return India	0.0000*	Stationary
Return Japan	0.0001*	Stationary

Note : * means significant at the 5% level.

(4) ARCH - LM Test : The presence of ARCH effect in the residuals has been tested with the help of ARCH LM test. The results of the test are presented in the Table 4. The p-value of the observed R-squared is significant for all return variables which shows that there is an ARCH effect present in the residuals and ,therefore, we may apply the ARCH/GARCH family models.

(5) GARCH (1, 1) Estimation : ARCH LM test confirms the presence of ARCH effect in residuals of all the return series ,therefore, the application of ARCH/GARCH model is justified. This section deals with the measurement of the ARCH and GARCH effect of each return variable. For this purpose, the GARCH (1, 1) model has been

Table 4. ARCH-LM Test

	Return China	Return Hong Kong	Return India	Return Japan
Observed *R*-squared	63.38198	120.00998	48.14081	209.9626
	(0.0000*)	(0.0000*)	(0.0000*)	(0.0000*)

Note : values in parentheses represent *p* - values ; significant at the 5% level

Table 5. GARCH (1, 1) Model for the Study Sample: 1/4/2008 to 28/10/2016

	Return China	Return Hong Kong	Return India	Return Japan
		Mean Equation		
Constant	0.013002 (0.6734)	0.039908 (0.1685)	0.058811 (0.0254*)	0.069230 (0.0253*)
AR(-1)	-0.031344 (0.2232)	-0.003280 (0.8974)	0.039605 (0.1002)	-0.031344 (0.2232)
		Variance Equation		
Constant	0.019818 (0.0001*)	0.025484 (0.0000*)	0.019942 (0.0000*)	0.097008 (0.0000*)
ARCH (1) A	0.055606 (0.0000*)	0.0643550 (0.0000*)	0.068509 (0.0000*)	0.128922 (0.0000*)
GARCH (1) B	0.938807 (0.0000*)	0.925562 (0.0000*)	0.921891 (0.0000*)	0.841964 (0.0000*)

Note : values in parentheses represent *p* - values ; significant at the 5% level

applied. The volatility of market return due to the impact of previous information is measured by ARCH coefficient and persistence of the return volatility is studied by GARCH coefficient. The results of the GARCH (1, 1) model are presented in the Table 5. From the Table 5, it may be observed that *p*-values of both ARCH and GARCH coefficients in variance equation are less than 0.05 for all the four countries. The sum of ARCH and GARCH coefficients is though less than one, but it is near to one, which means shocks in the markets are persistent and taking some time to die out. Taken as a whole, GARCH coefficients are much larger than the ARCH coefficients. This means that the previous volatility has a greater effect on the current volatility, while the persistence of the effect is weaker. Therefore, GARCH (1, 1) models are useful in modeling return in the return volatility.

(6) GARCH (1, 1) BEKK Estimation

$$h_{11,t} = 0.0208307354773 + 0.05706*U1\,(-1)\,\text{^}2+0.93731*h_{11,t-1} \quad (7)$$
$$h_{22,t} = 0.0257970749408 + 0.06575*U2\,(-1)\,\text{^}2+0.92441*h_{22,t-1} \quad (8)$$
$$h_{33,t} = 0.02042841893 + 0.06999*U3\,(-1)\,\text{^}2+0.92059*h_{33,t-1} \quad (9)$$
$$h_{44,t} = 0.096819202911+ 0.12767*U4\,(-1)\,\text{^}2+0.84320*h_{44,t-1} \quad (10)$$
$$h_{12,t} = 0.011739699541 + 0.06125*U1\,(-1)*U2\,(-1) + 0.93084*h_{12,t-1} \quad (11)$$
$$h_{13,t} = 0.00601657999864 + 0.06319*U1\,(-1)*U3\,(-1) + 0.92891*h_{13,t-1} \quad (12)$$
$$h_{14,t} = 0.0132954584074 + 0.08535*U1\,(-1)*U4\,(-1) + 0.88901*h_{14,t-1} \quad (13)$$
$$h_{23,t} = 0.0146493714509 + 0.06783*U2\,(-1)*U3\,(-1) + 0.92250*h_{23,t-1} \quad (14)$$
$$h_{24,t} = 0.0316083753466 + 0.09162*U2\,(-1)*U4\,(-1) + 0.88287*h_{24,t-1} \quad (15)$$
$$h_{34,t} = 0.0196751434149 + 0.09453*U3\,(-1)*U4\,(-1) + 0.88104*h_{34,t-1} \quad (16)$$

where, h stands for the conditional variance and U is the error term, 1-4 shows the country number.

The equations numbered from 7-10 are for the market specific volatility spillovers and equations from 11 to 16

Table 6. ARCH GARCH Coefficients for the Study Sample : 1/4/2008 to 28/10/2016

	Coefficient	Std. Error	*Z* - Statistic	Probability
C(China)	**8.38E-05**	0.000296	0.282514	0.7775
C(Hong Kong)	0.000516	0.000278	1.854508	0.0637**
C(India)	0.000641	0.000265	2.416431	0.0157*
C(Japan)	0.000582	0.000303	1.921268	0.0547**
		Variance Equation Coefficients		
C(5)	**2.56E-06**	**4.78E-07**	5.358104	0.0000*
C(6)	**1.79E-06**	**2.82E-07**	6.342888	0.0000*
C(7)	**5.80E-07**	**1.57E-07**	3.682445	0.0002*
C(8)	**1.69E-06**	**4.16E-07**	4.061677	0.0000*
C(9)	**3.59E-06**	**3.99E-07**	8.992488	0.0000*
C(10)	**1.26E-06**	**1.83E-07**	6.896955	0.0000*
C(11)	**3.42E-06**	**4.79E-07**	7.135527	0.0000*
C(12)	**1.13E-06**	**1.48E-07**	7.592809	0.0000*
C(13)	**1.94E-06**	**3.03E-07**	6.404509	0.0000*
C(14)	9.73E-06	**1.13E-06**	8.638744	0.0000*
C(15)	0.218607	0.007996	27.34061	0.0000*
C(16)	0.212856	0.006854	31.05604	0.0000*
C(17)	0.167283	0.006913	24.19889	0.0000*
C(18)	0.289584	0.010104	28.66039	0.0000*
C(19)	0.972613	0.001900	512.0107	0.0000*
C(20)	0.968586	0.001897	510.5972	0.0000*
C(21)	0.982651	0.001072	916.5631	0.0000*
C(22)	0.939198	0.003881	242.0013	0.0000*

Note :* significant at 5% level ; ** significant at 10% level

show the impact of cross market volatility spillovers. The log likelihood for the BEKK model is 22431, and the sum log likelihood for the four univariate GARCH models is 22031, which makes the model appropriate for interaction between the return volatility. The results of the GARCH BEKK model are given in the Table 6 and good interdependence between the selected markets can be observed from it. The constant conditional variance (from equations 7 to 10) $h_{11,t}$ is highest, which means there is greater risk in case of China in comparison to other countries included into the study. The values of $h_{22,t}$ and $h_{33,t}$ are almost similar to one another. Therefore, it may be inferred that both these markets, that is, Hong Kong and India are equally risky. Constant conditional variance is lowest for $h_{44,t}$. Thus, investments in stock markets of Japan are least risky.

The ARCH coefficient, which is the measure of the effect of the previous innovation on the conditional variance (0.12767) is highest for Japan (see equation 10). This proves that in comparison to other markets, volatility in markets of Japan is more sensitive to past market information. The lowest ARCH effect (0.05706) (see equation 7) is observed in China, which proves lesser sensitivity in stock markets of China. GARCH coefficient measures the persistence of return volatility or volatility clustering in a protracted period. The observed values of GARCH coefficients as given in equations 7 to 10 are 0.93731, 0.92441, 0.92059, and 0.84320 for China, Hong Kong, India, and Japan, respectively, which proves the existence of volatility clustering in all the countries. Among the four markets, the greatest degree of volatility clustering is seen in China and the least is seen in Japan. It leads to the conclusion that there is higher possibility that present volatility movement is related with its previous lag values in China and Japan in comparison to India and Hong Kong.

In covariance equations numbered from 11 to 16, the ARCH coefficients show the impact of the past common information or news to the current covariance, and GARCH coefficient presents the persistence of their return volatility concerning the covariance. Arch effect of 0.09453 is strongest between the markets of India and Japan.

This proves that previous information from the stock market of India will affect the Japanese market. Arch effect between Hong Kong and Japan (0.09162) is second strongest. The weakest ARCH effect (0.06125) is observed in China and Hong Kong, which means that among all the cross-market effects, information shared between the stock markets of Hong Kong and China has the least effect on their volatility. Highest volatility clustering (0.93084) has been observed between China and Hong Kong, which may perhaps be attributed to regional factors. The results of our study are similar to the results of the study carried by Liu and Giles (2015) in context of Asian developing nations and USA and the study of Agarwal (2017) in context of developed and developing nations. However, our results are not in consensus with the study results of Kumar and Kamaiah (2017) as their study measured return and volatility spillovers in Asian countries using the wavelet approach.

Discussion and Conclusion

This study examines the spillover effect in four major Asian countries namely China, Hong Kong, India, and Japan based on daily market indices of Hang Seng Composite for Hong Kong, Nikkei for Japan, Shanghai Composite Index for China, and Sensex for India. The data considered in the study were collected for a period from April 1, 2008 to October 28, 2016. The study has applied the GARCH BEKK model. The prominent findings of the study have been discussed here. According to the descriptive statistics, positive average returns in stock markets of India and Japan and negative average returns in stock markets of China and Hong Kong are observed. Maximum losses and high volatility in Chinese markets and maximum daily returns and lowest volatility in Indian markets are concluded from the study. The Chinese market suffered greatest fluctuations, and the Indian market was least affected by fluctuations. Among the four major markets, the Indian market is considered to be the most stable market.

Correlation between India and Hong Kong is the highest for the study period, which suggests strong regional economic integration in Hong Kong and India and similar growth patterns in two stock markets. Correlation between Japanese stock market and Hong Kong stock market is the second highest. Correlation between Indian and Chinese stock markets is least, which provides the conclusion that the two markets are least likely to move in relation to each other. In all the four Asian countries, GARCH coefficients are much larger than ARCH coefficients. This means that the previous volatility has a greater effect on the current volatility, while the persistence of the effect is weaker. In BEKK model, country-specific volatility and cross-country volatility spillover effects have been observed, and its results state that information is swiftly shared between stock markets of Hong Kong and Japan. Among the four Asian stock markets, the largest ARCH effect is also observed in Japan, which makes Japan more sensitive to past market information in comparison to other markets. The value of ARCH coefficient is lowest for China, thus making it less sensitive to past shocks or past information. GARCH coefficient, which measures the persistence of return volatility, is highest in case of China and least for Japan. In inter market comparisons, the ARCH effect is strongest between the markets of China and Japan and weakest between the markets of China and India, which leads to the conclusion that previous information from the stock markets of China and Japan will affect the Japan and China markets more, but information shared between the stock markets of India and China will have the least impact on their volatility. Persistency of cross market volatility is highest for the pair of China and India, and the same is lowest for the pair of China and Japan.

Research Implications

These findings have very important implications, notably for investor portfolio formation and trading decisions. Indeed, market participants should be aware of the relationship between international stock markets and the local stock market performance. For instance, the study findings suggest international portfolio diversification and trading decisions in India, China, Hong Kong, and Japan that should be taken into consideration to analyze the performance of major Asian stock markets. The main contribution of this paper is to provide direct evidence on the relationship between volatility in stock markets of India, China, Hong Kong, and Japan. An understanding of inter-market volatility is important for the pricing of securities within and across the markets for trading strategies, for hedging strategies, and for regulatory policy.

Limitations of the Study and Future Research Directions

The major limitation of the present study is that the results of this kind of studies are not static and may change with the change in the time period because of changes in the overall economic environment over a period of time. The present study examines volatility spillovers in only four major Asian stock markets - this can be extended to various other stock markets worldwide. The GARCH - BEKK model is used to conduct this study, which can be extended to various other ARCH-GARCH family models also. The study focuses only on developing stock markets of Asia, which can be extended to under developed stock markets of Asia and other parts of the world. The results of the study can be made more dynamic by quarterly assessments. The present study ignores the contagion aspect of volatility transmission, which can be taken up in future studies.

References

Adjasi, C. K. (2009). Macroeconomic uncertainty and conditional stock-price volatility in frontier African markets: Evidence from Ghana. *The Journal of Risk Finance, 10* (4), 333 - 349.

Agarwal, S. (2017). Volatility in stock markets: A comparison of developed and emerging markets of the world. *Indian Journal of Commerce and Management Studies, 8* (2), 87 - 92.

Ahmad, A., & Rana, U. S. (2012). Forecasting performance of various volatility models on intra-day equity price in the Indian stock market. *Indian Journal of Finance, 6*(6), 21-29.

Bae, K. H., Karolyi, G. A., & Stulz, R. M. (2003). A new approach to measuring financial contagion. *The Review of Financial Studies, 16* (3), 717 - 763.

Baele, L. (2005). Volatility spillover effects in European equity markets. *Journal of Financial and Quantitative Analysis, 40* (2), 373 - 401.

Baumöhl, E., & Lyócsa, Š. (2014). Volatility and dynamic conditional correlations of worldwide emerging and frontier markets. *Economic Modelling, 38* (C), 175-183.

Bauwens, L., Laurent, S., & Rombouts, J. V. (2006). Multivariate GARCH models: A survey. *Journal of Applied Econometrics, 21*(1), 79-109.

Beirne, J., Caporale, G. M., Schulze - Ghattas, M., & Spagnolo, N. (2009). *Volatility spillovers and contagion from mature to emerging stock markets* (Working Paper Series 1113). European Central Bank. Retrieved from https://ideas.repec.org/p/ecb/ecbwps/20091113.html

Bekiros, S. D. (2014). Contagion, decoupling and the spillover effects of the US financial crisis: Evidence from the BRIC markets. *International Review of Financial Analysis, 33,* 58 - 69.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327.

Bordo, M. D., & Murshid, A. P. (2006). Globalization and changing patterns in the international transmission of shocks in financial markets. *Journal of International Money and Finance, 25* (4), 655 - 674.

Campbell, J. Y., & Hamao, Y. (1992). Predictable stock returns in the United States and Japan : A study of long - term capital market integration. *The Journal of Finance, 47*(1), 43 - 69.

Donadelli, M. (2015). Asian stock markets, US economic policy uncertainty and US macro-shocks. *New Zealand Economic Papers, 49* (2), 103-133.

Drew, M. E., Naughton, T., & Veeraraghavan, M. (2003). Firm size, book-to-market equity and security returns: Evidence from the Shanghai Stock Exchange. *Australian Journal of Management, 28* (2), 119 - 139.

Dungey, M., & Martin, V. L. (2007). Unravelling financial market linkages during crises. *Journal of Applied Econometrics, 22* (1), 89 - 119.

Errunza, V., & Losq, E. (1985). International asset pricing under mild segmentation: Theory and test. *The Journal of Finance, 40* (1), 105 -124.

Faff, R. W., & McKenzie, M. D. (2007). The relationship between implied volatility and autocorrelation. *International Journal of Managerial Finance, 3* (2), 191-196.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48* (5), 1779 - 1801.

Hafner, C. M., & Reznikova, O. (2012). On the estimation of dynamic conditional correlation models. *Computational Statistics & Data Analysis, 56* (11), 3533 - 3545.

Hamao, Y., Masulis, R. W., & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies, 3* (2), 281-307.

Johansson, A. C., & Ljungwall, C. (2009). Spillover effects among the Greater China stock markets. *World Development, 37*(4), 839-851.

Jorion, P., & Schwartz, E. (1986). Integration vs. segmentation in the Canadian stock market. *The Journal of Finance, 41*(3), 603 - 614.

Joshi, P. (2011). Return and volatility spillovers among Asian stock markets. *SAGE Open, 1*(1), 1-8.

Kenourgios, D. (2014). On financial contagion and implied market volatility. *International Review of Financial Analysis, 34,* 21 - 30.

Khuong Nguyen, D., & Bellalah, M. (2008). Stock market liberalization, structural breaks and dynamic changes in emerging market volatility. *Review of Accounting and Finance, 7* (4), 396 - 411.

Koutmos, G. (2012). Modeling interest rate volatility: An extended EGARCH approach. *Managerial Finance, 38* (6), 628 - 635.

Kumar, A. S., & Kamaiah, B. (2017). Returns and volatility spillover between Asian equity markets: A wavelet approach. *Economic Annals, 62* (212), 63 - 83.

Kumar, S. S. S. (2012). A first look at the properties of India's volatility index. *International Journal of Emerging Markets, 7*(2), 160-176.

Li, Y., & Giles, D. E. (2015). Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets. *International Journal of Finance & Economics, 20* (2), 155-177.

Liu, C. (2016). Spillover effects in major equity markets: A GARCH BEKK approach. *Open Access Library Journal, 3* (2), 1-21.

Liu, Y. A., & Pan, M. S. (1997). Mean and volatility spillover effects in the US and Pacific - Basin stock markets. *Multinational Finance Journal, 1*(1), 47-62.

Mensi, W., Beljid, M., Boubaker, A., & Managi, S. (2013). Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling, 32,* 15 - 22.

Mishra, A. K. (2004). Stock market and foreign exchange market in India : Are they related? *South Asia Economic Journal, 5* (2), 209 - 232.

Nakatani, T., & Teräsvirta, T. (2009). Testing for volatility interactions in the constant conditional correlation GARCH model. *The Econometrics Journal, 12* (1), 147-163.

Narayan, S., Sriananthakumar, S., & Islam, S. Z. (2014). Stock market integration of emerging Asian economies: Patterns and causes. *Economic Modelling, 39,* 19-31.

Narula, I. (2016). Dynamics of volatility behaviour and transmission: Evidences from BRICS countries. *Decision, 43* (1), 31-51.

Ng, A. (2000). Volatility spillover effects from Japan and the US to the Pacific - Basin. *Journal of International Money and Finance, 19*(2), 207-233.

Patel, R. J. (2017). Co-movement and integration among stock markets: A study of 14 countries. *Indian Journal of Finance, 11*(9), 53 - 66. doi:10.17010/ijf/2017/v11i9/118089

Rajan, M. P. (2011). Volatility estimation in the Indian stock market using heteroscedastic models. *Indian Journal of Finance, 5* (6), 26 - 32.

Rao, A. (2008). Analysis of volatility persistence in Middle East emerging equity markets. *Studies in Economics and Finance, 25*(2), 93 - 111.

Rittler, D. (2012). Price discovery and volatility spillovers in the European Union emissions trading scheme: A high-frequency analysis. *Journal of Banking & Finance, 36* (3), 774 - 785.

Shamiri, A., & Isa, Z. (2010). Volatility transmission: What do Asia-Pacific markets expect? *Studies in Economics and Finance, 27*(4), 299 - 313.

Singh, A., & Kaur, P. (2015). Modelling dynamic volatility spillovers from the U.S. to the BRIC countries' stock markets during the subprime crisis. *Indian Journal of Finance, 9*(8), 45-55. doi:10.17010/ijf/2015/v9i8/74562

Tuan, T. K., Hwa, Y. S., Chua, S. Y., & Lean, H. H. (2015). Do Indian economic activities impact ASEAN-5 stock markets? *Jurnal Ekonomi Malaysia, 49*(2), 61 - 76.

Wang, P., & Wang, P. (2010). Price and volatility spillovers between the greater China markets and the developed markets of US and Japan. *Global Finance Journal, 21*(3), 304 - 317.

Wei, K. J., Liu, Y. J., Yang, C. C., & Chaung, G. S. (1995). Volatility and price change spillover effects across the developed and emerging markets. *Pacific-Basin Finance Journal, 3* (1), 113 - 136.

Zhou, X., Zhang, W., & Zhang, J. (2012). Volatility spillovers between the Chinese and world equity markets. *Pacific-Basin Finance Journal, 20* (2), 247 - 270.

About the Authors

Dr. Ashish Kumar is an Assistant Professor in Finance at University School of Management Studies (USMS), GGSIP University, New Delhi. He obtained his Ph.D. in Finance from Maharishi Dayanand University, Rohtak, Haryana. His industry and academic experience extends to 18 years. He is a keen researcher and has contributed more than 40 research papers and articles in journals of national and international repute.

Swati Khanna is an Assistant Professor in the area of Finance at Northern India Engineering College affiliated to GGSIPU, New Delhi and is a Research Scholar under the guidance of Dr. Ashish Kumar, GGSIPU. Her industry and academic experience extends to 8 years.