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VOLATILITY SPILLOVER AND TIME-VARYING CORRELATION AMONG THE INDIAN, ASIAN AND US STOCK MARKETS

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Abstract

Transmission mechanisms presenting between returns and volatilities play a critical role in examining the distribution and interdependence across international financial markets. Our objective is to investigate volatility transmission between emerging markets in geographically disparate regions. The data used in this study are daily stock-price indices from July 1, 1994, through September 30, 2009, for five Asia equity markets, India and United States. We have used bivariate BEKK and DCC model for the analysis. Bilateral shocks and volatility spill over existing in the India/Malaysia, India/Taiwan and India/Indonesia. Evidence demonstrates that Indonesia is the main transmitter within the Asia markets. The significance of DCC-GARCH estimates explains that conditional correlation between India and the Asia-US stock markets are highly dynamic and time varying.

Keywords: International Financial Markets, Spillover, Dynamic Conditional Correlation

JEL Classification: F21;C22; G15

1. Introduction

A salient feature involved in the volatility spillover phenomenon is that markets tend to move closer together especially when markets become agitated. Moreover the analysis of financial market integration, co-movement and the degree of correlation between assets plays a vital role in many financial decisions for market participants such as international trading companies and financial institutions. For example, the increased correlation between international assets may diminish the diversity of an international investment portfolio. This might force market participants to seek relative independent assets to maintain the optimal portfolio selection. However the fact that the pronounced features of financial asset prices are well-recognized and documented by economists results in obstacles to researchers obtaining an accurate estimation of financial co-movement and correlations. These features include volatility clustering, leptokurtosis and time-varying characteristics. Therefore there is a need for us to investigate the

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volatility spillovers and dynamic conditional correlations by using advanced econometric approaches.

Transmission mechanisms presenting between returns and volatilities play a critical role in examining the distribution and interdependence across international financial markets. Due to the following explicit and implicit reasons summarized by Harris and Pisedtasalasai (2005): firstly transmission mechanism is an indicator of market efficiency. If spillovers are found in a return series then it is possible to exploit strategy profits which are against the market efficiency criteria. Secondly, it is acknowledged that information about return spillover effects is helpful to allocate assets and to construct portfolios. Thirdly understanding of volatility spillovers is crucial when dealing with those financial applications requiring for estimation of conditional volatility such as derivations pricing and value at risk (VaR) estimation.

Our objective is to investigate volatility transmission between emerging markets in geographically disparate regions, we select emerging Asian markets to answer and test the following research questions and hypothesis: whether volatility spillover effects exist between the Asian markets, US and Indian market? Who is (are) the main volatility transmitter(s) during the past fifteen years?. How the time-varying conditional correlations differ from unconditional correlation in terms of magnitude and direction? Is the time varying conditional correlation between stock index return series mean-reverting?

Comparatively little has been done on volatility co-movement between the Indian stock market and that of the US, UK and Asia. It is the limited nature and paucity of such work in the existing literature that has spurred us to investigate the volatility co-movement of the Indian market with major stock markets.

The remainder of the paper proceeds as follows. Section 2 describes the review of literature. Section 3 explains the dynamic conditional correlation and BEKK methodology and data. Section 4 presents the descriptive statistics and estimation results. Section 5 contains the conclusion.

2. Review of Literature

It is fairly well established that stock traders in a given market incorporate into their ‘buy’ and ‘sell’ decisions not only information generated domestically but also information produced by other stock markets. Such behavior is consistent with the efficient market hypothesis, provided that news generated in international stock market is relevant for the pricing of domestic securities. This is the result of globalization of financial markets, brought about by the relatively free flow of goods and capitals as well as revolution in information technology. Understanding the ways in which stock markets interact and permits investors to carry out hedging and trading strategies more successfully (Koutmos and Booth, 1995).

Given the increasing inter-linkages between national financial markets brought about by trade and financial liberalization, our intention is to investigate volatility transmission in stock market returns across emerging markets in Asia and US.

Equity market integration is likely to increase the covariance of returns across borders. As noted by Karolyi and Stulz (1996), an increase in covariance will affect the volatility of portfolios and the price of assets. *A priori* volatility may increase because greater covariance reduces the opportunities for investors to diversify their portfolios internationally. Eun and Shim (1989) explain that ‘unexpected developments in international stock markets seem to have become important “news” events that influence domestic stock markets’. That event in one equity market may produce significant reactions in another market is termed stock market interdependence or spillover effect. Historically, the correlation between emerging market returns and international returns tended to be low which presented investors with significant opportunities for portfolio diversification. However, recent empirical studies find correlations are time-varying (Bekaert and Harvey, 1997), yet there is no clear increase in the co-movement of returns (Bae et al, 2003; Karolyi, 2001) though the correlation between emerging markets is reported to have increased (Bekaert and Harvey, 2002). Hamao et.al (1990) examine price spillovers (i.e. first-moment interdependencies) and volatility spillovers (i.e, second-moment interdependencies) in the three major stock markets (New York, Tokyo, and London) using univariate GARCH models.

The characteristics of emerging equity markets are different from developed markets, for instance, the former tend to be smaller and less liquid. Similarly, emerging market equity returns also differ from their developed counterparts. Generally speaking, mean returns in emerging markets tend to be higher; they have low correlations with global markets; emerging market returns are more predictable; and their volatility is higher (Bekaert and Harvey, 1997). A leading question is why volatility is so different in emerging markets. Volatility has implications for asset allocation decisions. In a segmented market, risk premiums might be directly related to the volatility of returns in that market. Consequently, higher volatility implies higher capital costs; this feature could increase the value of delaying an investment, the so-called option-to-wait. Bekaert et al (2002) find that equity market liberalization is associated with higher average returns and lower volatility in emerging markets although not in all. Whereas the correlation between returns in emerging markets and global markets tends to increase after liberalization, the correlation remains fairly low suggesting potential diversification benefits still exist in emerging market equities.

Koutmos and Booth (1995) examine the spillover effects among the New York, Tokyo and London stock markets and shows the transmission of volatility is asymmetric and is more pronounced when the news is bad and coming from either US or UK market. Kanas (1998) studies on the transmission effects among the London, Paris and Frankfurt stock markets and concludes that returns and innovations spillovers are higher during the post-crash time. Billio and Pelizzon (2003) obtain evidence showing that volatility spillover from the world index return series have increased after the introduction of the EMU (European Monetary Union) for most European stock market. Christiansen (2007) investigates volatility spillover from the US and aggregate European asset markets into European national asset markets with the innovation of incorporating the bond markets into the analysis. Koulakiotis, Dasilas and Papasyriopoulos (2009) find evidence of volatility and error transmission spillover effects from three European financial regions and claim that each region has its own main exporter. Among the numerous literatures, two types of multivariate GARCH model are extremely popular. Some researchers are using a multivariate extension of Nelson (1991) univariate exponential GARCH (EGARCH) which allows for time-varying correlation. Whereas, some academicians prefer the BEKK (Engle and Kroner, 1995) model which is famous for the superiority and flexibility of modeling spillover effects for low dimensions (Alexander, 2008).

Some empirical evidence suggests the more developed Asian markets in Japan, Korea and Taiwan became more integrated with the US market by 1997. Masih and Masih (1999) expand on the latter point claiming that international equity markets lead developed and emerging Asian markets. Whereas the US is found to lead Asian markets, the contemporaneous co-movement between Asian markets and Japan is greater. Whilst Asian equity markets react to shocks from the US and Japanese markets, the US increased in importance following the 1997 crisis (Tan and Tse, 2002). Nevertheless, the importance of the Japanese equity market in the regional context is noted by Jang and Sul (2002) and Fernández-Serrano and Sosvilla-Rivero (2001). Specifically, the role that trade linkages play in enhancing financial linkages is suggested as a reason for increases in the co-movement of Japanese and regional equity returns; an increased export share to Japan by regional economies, and greater foreign direct investment from Japan to other Asian countries (Johnson and Soenen, 2002). On the contrary, co-movement decreases because of factors such as differentials in inflation, real interest rates and GDP.

Ng (2002) provides evidence that emerging Asian equity markets in Indonesia, the Philippines and Thailand have become more closely linked to Singapore, and that generally speaking, the correlation of equity market returns across ASEAN markets increased over a period following equity market liberalization. Susmel and Engle (1994) examine price and volatility spill over between New York and London using hourly returns. They conclude that these spillovers are, at best, small and of short duration.

3. Data and Methodology

The data used in this study are daily stock-price indices from July 1, 1994, through September 30, 2009, for five Asia equity markets, India and United States. The data set consists of the stock indices of Thailand (Bangkok S.E.T. Index), Malaysia (Kuala Lumpur SE Index), Indonesia (Jakarta SE Composite Index), Taiwan (Taiwan SE Weighted Index), India (BSE), and the United States (S&P 500 Composite Index). All the national stock price indices are in local currency, dividend-unadjusted, and based on daily closing prices in each national market. All the data were obtained from the Reuter's database.

3.1 DCC-GARCH Model

Simple (or rolling) correlation analysis is among the simplest method for examining the co-movement of financial markets. Basically, higher degree of correlation between markets implies higher co-movement and greater integration between the markets. The DCC model, proposed by Engle and Sheppard (2001) and Engle (2002), is a new class of multivariate model which is particularly well suited to examine correlation dynamics among assets. The DCC approach has the flexibility of univariate GARCH but without the complexity of a general multivariate GARCH. As the parameters to be estimated in the correlation process are independent of the number of series to be correlated, a large number of series can be considered in a single estimation.

Following Bollerslev (1990), Engle and Sheppard (2001) and Engle (2002) we start our empirical specification with the assumption that stock market returns from the k series are multivariate normally distributed with zero mean and conditional variance-covariance matrix H_t. Our multivariate DCC-GARCH model can be presented as follows:

$$r_t = \mu_t + \varepsilon_t \qquad \text{... (1)}$$

with $\varepsilon_{t} / \Omega_{t-1} \rightarrow N(0, H_t)$ where, r_t is the (k×1) vector of the returns, ε_t is a (k×1) vector of zero mean return innovations conditional on the information, Ω_{t-1}, available at time t-1 and the conditional variance-covariance matrix (H_t) in the DCC model can be expressed as:

$$H_t = D_t R_t D_t \qquad \text{... (2)}$$

where D_t represents a (k×k) diagonal matrix of the conditional volatility of the returns on each asset in the sample and R_t is the (k×k) conditional correlation matrix. Basically, the DCC-GARCH model estimates conditional volatilities and correlations in two steps. In the first step the mean equation of each asset in the sample, nested in a univariate GARCH model of its conditional variance is estimated. Hence, we can define D_t as follows:

$$D_t = (h_{iit}^{1/2} \ldots\ldots\ldots h_{kkt}^{1/2}) \qquad \text{... (3)}$$

where $h_{iit,}$ conditional variance of each asset, is assumed to follow a univariate GARCH (p_i, q_i) process, given by the following expression:

$$h_{i,t+1} = \omega_i + \sum_{p=1}^{p_i} \alpha_{i,p} \; \varepsilon^2_{i,t+1-p} + \sum_{q=1}^{q_i} \beta_{i,q} h_{i,t-q} \qquad \text{.. (4)}$$

however, to insure non-negativity and stationarity some restrictions, such as:

$$\alpha_{i,p} > 0 \;,\; \beta_{i,q} > 0 \quad \text{and} \quad \sum_{p=1}^{p_i} \alpha_{i,p} \; \varepsilon^2_{i,t+1-p} + \sum_{q=1}^{q_i} \beta_{i,q} h_{i,t-q} < 1$$

should be imposed. These uni-variate variance estimates are then used to standardize the zero mean return innovations for each asset.

In the second stage, stock return residuals are transformed by their estimated standard deviations from the first stage. That is $u_{i,t} = \varepsilon_{i,t} \big/ \sqrt{h_{ii,t}}$ where $u_{i,t}$ is then used to estimate the parameters of the conditional correlation. The evolution of the correlation in the DCC model is given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \qquad \text{... (5)}$$

where Q_t refers to a (k×k) time varying covariance matrix of $u_{i,t}$, $\bar{Q}$ is the (k×k) unconditional variance matrix of $u_{i,t}$, and α and β are nonnegative scalar parameters satisfying α + β < 1.

Since Q_t does not generally have ones on the diagonal, we scale it to obtain a proper correlation matrix R_t. Thus,

$$R_t = (\mathrm{diag}(Q_t))^{-1/2} Q_t (\mathrm{diag}(Q_t))^{-1/2} \qquad \text{... (6)}$$

where $(\mathrm{diag}(Q_t))^{-1/2} = \mathrm{diag}\,(1\big/\sqrt{q_{11,t}} \ldots\ldots\ldots\ldots 1\big/\sqrt{q_{nn,t}}\,)$

Finally, the conditional correlation coefficient ρ_{ij} between two assets i and j is then expressed by the following equation:

$$\rho_{ij,t} = q_{ij,t} \Big/ \sqrt{q_{ii,t} q_{jj,t}} \;, \quad i,j = 1,2,.........,n, \text{and } i \neq j \qquad ... (7)$$

Expressing the correlation coefficient in a bivariate case, we have:

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha u_{1,t-1} u_{2,t-1} + \beta q_{12,t-1}}{\sqrt{[(1-\alpha-\beta)\bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1}]}\sqrt{[(1-\alpha-\beta)\bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1}]}} \qquad ... (8)$$

As per Engle and Sheppard (2001) and Engle (2002), the DCC model can be estimated by using a two – stage approach to maximizing the log - likelihood function. Let *θ* denote the parameters in D_t and ϕ the parameters in R_t , then the log likelihood function is given below:

$$l_t(\theta,\varphi) = [-\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|D_t|^2 + \varepsilon_t^{'} D^{-2} \varepsilon_t)] + [-\frac{1}{2}\sum_{t=1}^{T}(\log(2\pi) + \log|R_t| + u_t^{'} R_t^{-1} u_t - u_t^{'} u_t)] \qquad ... (9)$$

The first part of the likelihood function in equation (9) is volatility, which is the sum of individual GARCH likelihoods. The log – likelihood function can be maximized in the first stage over the parameter in D_t. Given the estimated parameters in the first stage, the correlation component of the likelihood function in the second stage (the second part of the equation (9) can be maximised to estimate correlation coefficients.

3.2 BEKK-GARCH Model

BEKK-GARCH Model is an extension of the bivariate GARCH model which can capture volatility transmission among different series, as well as the persistence of volatility within each series. In the present study to examine the volatility transmission i.e. spillover effects within and between emerging equity markets in Asia we use a bivariate BEKK(Baba-Engle-Kraft-Kroner) GARCH (1,1) model proposed by Engle and Kroner (1995).

In our study we will use ARMA (1,1) to define the conditional mean of the returns. Thus according to Engle and Kroner (1995) the ARMA (1,1) – BEKK (1,1) model takes the following form:

$$r_{it} = \alpha + \varphi_{i,t-1} r_{i,t-1} + \varepsilon_{it} + \theta \varepsilon_{i,t-1} \qquad i = 1,2,3,4 \qquad ... (10)$$

$$\varepsilon_t / \Omega_t \sim N(0, H_t)$$

$$H_t = C_0^{'} C_0 + A_{11}^{'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A_{11} + B_{11}^{'} H_{t-1} B_{11} \qquad ... (11)$$

Where r_t is a T by 1 vector of asset returns, ε_{it} is the innovation term in the return equation, Ω_t is the matrix of conditional previous information set and H_t is the variance-covariance matrix of the residuals term from Eq. (1) and it's guaranteed to be positive because the BEKK model uses a quadratic form for the parameter matrices to ensure a positive definite variance- covariance matrix. The parameter vector consists of elements of C which is a lower triangular matrix; n × n matrix A_{11} is showing ARCH effects and n× n matrix B_{11} which reveal the GARCH effects. So the matrix form of equation(10) is as follows

$$H_t = C_0'C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{s,t-1} & \varepsilon_{s,t-1},\varepsilon_{f,t-1} \\ \varepsilon_{s,t-1},\varepsilon_{f,t-1} & \varepsilon^2_{s,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \qquad ...(12)$$

The diagonal elements in the parameter matrix B measure the effect of lagged volatility; the off-diagonal elements capture the cross market effects. Therefore, the BEKK model is very desirable to examine volatility spillover effects.

Compared with the BEKK model, the prominent strength of the DCC model is that it does not suffer dimension hindrance and could be applied to any dimension. This is because the estimation can be decomposed into two steps: firstly is estimating the univariate GARCH and subsequently constructing a maximum likelihood function which has only two parameters . However the DCC model imposes more restrictions on the type of dynamic effects than the BEKK model.

In particular the conditional variance of returns only depends on the past squared returns, some of which can cause the volatility spillovers to be excluded. Similarly, feedback from past volatilities or squared returns on correlations is severely limited in the DCC model. Using a multivariate BEKK GARCH model, we investigate volatility transmission i.e. spillover effects within and between emerging equity markets in Asia. Our approach allows cross-border spillover effects to vary over time. We choose the Engle and Korner (1995) model to capture the volatility spillover effects and DCC model to measure the dynamic conditional correlation.

4. Empirical Analysis

Descriptive statistics are reported in Table 1. The sample mean of the returns is positive and statistically significant except Thailand. The variance ranges from 0.3754 (Japan) to 1.7135 (China). The skewness is negative for eight indices and positive for Malaysia and Thailand. The kurtosis indicates the returns are leptokurtic. The Jarque-Bera statistics rejects normality at any level of statistically significance in all cases. The Ljung-Box statistics for 14 lags applied on returns (denoted by LB (14)) and squared returns (denoted by LB^2 (14)) indicate that significant linear and nonlinear dependencies exist. Linear dependence may be due to some form of market inefficiency (Koutmos and Booth, 1995). Non linear dependencies can be satisfactorily captured by autoregressive conditional heteroscedasticity (ARCH) models. As the Q statistics are highly significant, we report the presence of autocorrelation upto lag 14 and suggest the application of the BEKK GARCH model is appropriate.

In table 2, the off-diagonal elements of matrices A and B measures the cross market effects such as shock and volatility spillover effects among the eleven stock markets. First we claim that bilateral shock and volatility spillover effects exist in the case of India/Malaysia, India/Taiwan and India/Indonesia. Out of the four cross market effects, three are significant. It is consistent with the previous literature in that volatility effect are not symmetric. There is no similar pattern emerge out of these cross correlation coefficients. Evidence demonstrates that the Indonesia market is the main transmitter within the Asian market. In particular, B_{12} (0.4486) in Indonesia/India indicates the level of highest volatility transmission among the five indices. Volatility transmission from Indonesia to India is 44.86% which implies that a 1% increase in the return of the Indonesia index transmit 44.86% volatility to India, which is the highest among all the five markets. B_{21} coefficient is insignificant in the case of Thailand, Indonesia and US. The coefficient shows the persistence characteristics for all the indices.

Table 1. Descriptive Statistics

	IND	*USA*	*MAL*	*TWN*	*THA*	*IDO*
Mean	0.0369	0.0224	0.0047	0.0050	-0.0152	0.0436
Median	0.0991	0.0463	0.0161	0.0231	-0.0342	0.0670
Maximum	15.9900	10.9572	20.2595	8.5198	21.5422	10.6917
Minimum	-11.8092	-9.4695	-24.1534	-9.9360	-16.0633	-12.7321
Std. Dev.	1.6864	1.2527	1.4611	1.5735	1.6885	1.6318
Skewness	-0.0459	-0.2012	0.0379	-0.1128	0.4493	-0.2395
Kurtosis	8.4570	11.6810	43.2711	5.5590	15.3596	9.6060
Jarque-Bera	4789.62	12143.33	260766.90	1061.12	24692.41	7053.74
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LB-Q(4)	35.453	27.466	75.426	29.523	61.699	166.94
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LB-Q(14)	73.698	61.218	90.367	59.895	103.24	196.01
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LB-Q^2(4)	307.94	1031.7	2296.8	305.64	252.84	620.24
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LB-Q^2(14)	635.86	3978.7	2646.8	660.58	447.87	1350
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	3859	3859	3859	3859	3859	3859

Note: p values are in paranthesis. LB-Q (*p*) is the statistics of Ljung-Box Q test for the null hypothesis that there is no auto-correlation in a return series at lag *p*. LB-Q^2 (*p*) is the same test to detect any departure from the white noise behavior of the squared return series.

Source: Authors' calculations.

Table 2. Results of the Bivariate BEKK Model for the India Verses US & Asian Equity Markets

country→ *Parameters↓*	*IND/USA*	*IND/MAL*	*IND/TWN*	*IND/THA*	*IND/IDO*
C(1,1)	0.257119*	0.268554*	0.257214*	0.238963*	0.225019*
	[0.02371]	[0.02824]	[0.02341]	[0.02385]	[0.02403]
C(2,1)	0.025619***	-0.05954*	0.156662*	0.168582*	-0.17669*
	[0.01513]	[0.01241]	[0.01659]	[0.04362]	[0.02387]
C(2,2)	0.078702*	-6.60E-06	-0.00323	0.304931*	-0.0002
	[0.01073]	[0.12744]	[0.01358]	[0.01723]	[0.47268]
A(1,1)	0.32702*	0.327942*	0.340900*	0.310034*	0.27827*
	[0.01608]	[0.02114]	[0.01797]	[0.01769]	[0.01681]
A(1,2)	0.023946**	0.003541	0.124735*	0.012418	-0.02632**
	[0.00855]	[0.00931]	[0.01198]	[0.01514]	[0.01257]
A(2,1)	0.007416	0.049868*	-0.00494	0.01029	0.042612*
	[0.02367]	[0.01385]	[0.01632]	[0.01825]	[0.01329]
A(2,2)	0.229758*	0.302266*	-0.178200*	0.310816*	0.337366*
	[0.01144]	[0.01696]	[0.01161]	[0.01027]	[0.01844]
B(1,1)	0.935616*	0.94245*	0.920282*	0.945327*	0.954296*
	[0.00641]	[0.01023]	[0.00693]	[0.00645]	[0.01451]
B(1,2)	-0.00959*	-0.22514*	0.416615*	-0.00156	0.448646*
	[0.00324]	[0.02073]	[0.02497]	[0.00460]	[0.04524]
B(2,1)	0.000443	0.091417**	0.050709*	-0.0142	-0.0224
	[0.00633]	[0.04370]	[0.00019]	[0.00913]	[0.05420]
B(2,2)	0.971339*	0.966395*	-0.971100*	0.927564*	-0.9407*
	[0.00288]	[0.00627]	[0.00242]	[0.00237]	[0.01343]

Note: The statistics reported in the parenthesis is Standard Error. The parenthesis shows the 'standard error' statistics and the asterisk *, ** and *** reveal significant coefficients at 1%, 5% and 10% levels, respectively.
Source: Authors' calculations.

One of the objectives of this study is to investigate the dynamic conditional correlation mechanism between Asia and India equity markets. The maximum likelihood estimates of the dynamic conditional correlation model for the Asia-US are reported in table 3. The bivariate DCC model applied in the analysis allows for a time varying correlation structure. Parameter μ correspond to the mean equation while ω, α and β represents the conditional variance of equity returns of India versus Asia and US. All parameters are found to be highly significant and positive, the significance of mean equation parameter μ shows the dependence of returns on their lag returns. Variance equation parameters α and β support our modeling technique, i.e., bivariate GARCH analysis, by revealing the presence of conditional heteroskedasticity in the time series. Again GARCH (1, 1) parameters are highly significant confirming the time varying variance covariance process as well as strengthening the use of bivariate GARCH modeling for Asia-US stock market data.

The volatility persistence in these markets is measured by ($\alpha + \beta$). The values of the above coefficients in table 4 provide evidence of strong volatility persistence in all the countries. The estimated coefficients are significant and close to one for all the countries. All ($\alpha + \beta$) coefficients are less than one, a necessary condition for the unconditional variance to be finite. Similar to the parameters obtained usually from the estimation of the conditional variance process, the ARCH parameter δ_{DCC1} in the conditional correlation equation are generating small, positive and significant values. The GARCH parameter δ_{DCC2} are large and close to one indicating that time-varying correlation exhibits a high degree of persistence. Empirical evidence by King and Wadhwani (1990) suggest that an increase in volatility leads in turn to an increase in the size of the spillover effects. Finally, the significance of DCC-GARCH estimates δ_{DCC1} and δ_{DCC2} explains that conditional correlation between India and the Asia-US stock markets are highly dynamic and time varying.

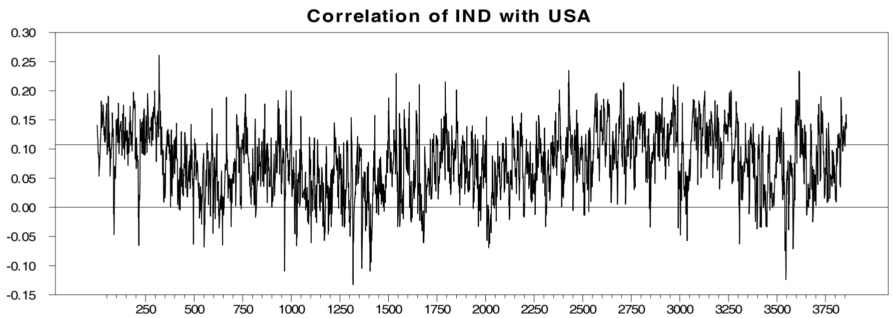
Table 3. Results of the Bivariate DCC Model for the Indian versus US & Asian Equity Markets

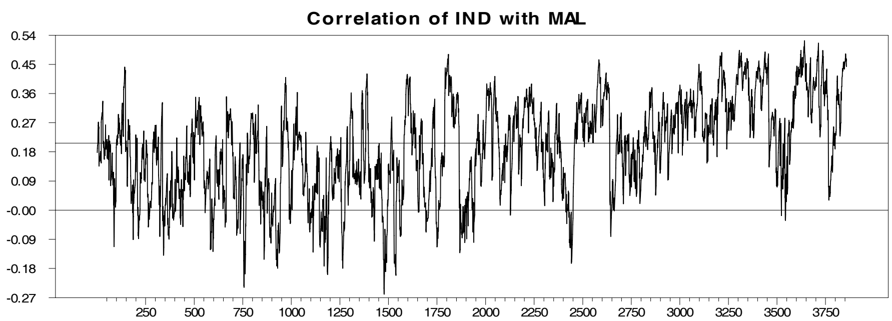
country→ *Parameter↓*	*IND/USA*	*IND/MAL*	*IND/TWN*	*IND/THA*	*IND/IDO*
μ_1	0.0463* [0.009]	0.0444* [0.008]	0.0434* [0.008]	0.0426* [0.009]	0.0424* [0.008]
μ_2	0.0268* [0.006]	0.0173* [0.005]	0.0221* [0.009]	0.0145* [0.009]	0.0434* [0.008]
ω_1	0.0111* [0.001]	0.0170* [0.001]	0.0105* [0.001]	0.0105* [0.001]	0.0101* [0.001]
ω_2	0.0018* [0.0002]	0.0021* [0.0003]	0.0069* [0.0009]	0.0238* [0.0017]	0.0174* [0.001]
α_1	0.1220* [0.006]	0.1212* [0.006]	0.1156* [0.005]	0.1129* [0.006]	0.1145* [0.006]
α_2	0.0716* [0.0054]	0.1228* [0.005]	0.0685* [0.004]	0.1126* [0.009]	0.1609* [0.008]
β_1	0.8645* [0.006]	0.8656* [0.006]	0.8713* [0.005]	0.8734* [0.005]	0.8733* [0.005]
β_2	0.9225* [0.0058]	0.8793* [0.004]	0.9176* [0.006]	0.8425* [73.033]	0.8102* [0.007]
$\delta_{DCC\,(1)}$	0.0045* [0.002]	0.0316* [0.005]	0.0060* [0.002]	0.0174* [0.003]	0.0092* [0.002]
$\delta_{DCC\,(2)}$	0.9939* [0.003]	0.9529* [0.008]	0.9936* [0.002]	0.9735* [0.005]	0.9886* [0.003]

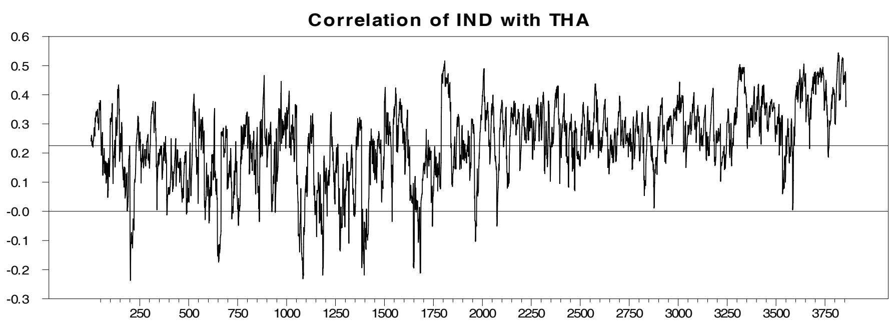
Note: The statistics reported in the parenthesis is Standard Error. The parenthesis shows the 'standard error' statistics and the asterisk *, ** and *** reveal significant coefficients at 1%, 5% and 10% levels, respectively.

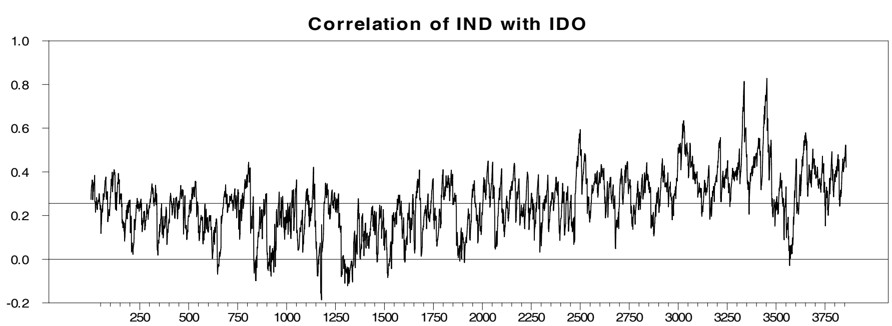
Source: Authors' calculations.

The graph shows the pattern of the dynamic conditional correlation, which are reported below.









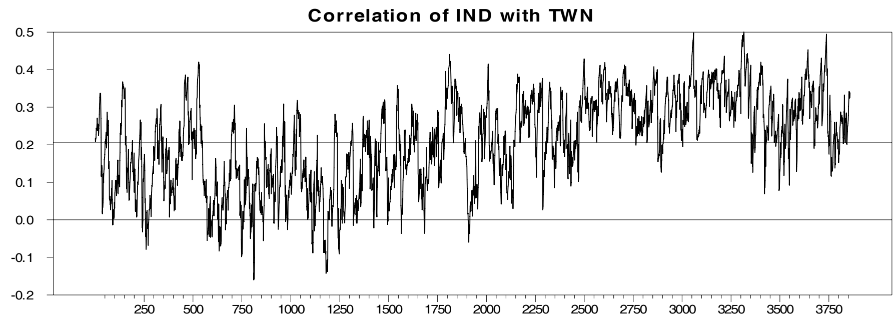


Figure 1. Dynamic Conditional Correlations obtained from DCC-GARCH Analysis

5. Conclusion

In this paper we try to investigate the presence of volatility spill over and dynamic conditional correlation between India/US, India/Malaysia, India/Taiwan, India/Thailand and India/Indonesia. The Ljung-Box statistics for 14 lags applied on returns (denoted by LB (14)) and squared returns (denoted by LB^2 (14)) indicate that significant linear and nonlinear dependencies exist. Linear dependence may be due to some form of market inefficiency (Koutmos and Booth, 1995). Bilateral shocks and volatility spillover exist in the India/Malaysia, India/Taiwan and India/Indonesia. Evidence demonstrates that Indonesia is the main transmitter within the Asia markets. The significance of DCC-GARCH estimates δ_{DCC1} and δ_{DCC2} explains that conditional correlation between India and the Asia-US stock markets are highly dynamic and time varying. The graphs depict the time varying correlation between different markets.

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