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A STUDY OF VOLATILITY SPILLOVER ACROSS SELECT FOREIGN EXCHANGE RATES IN INDIA USING DYNAMIC CONDITIONAL CORRELATIONS

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Abstract

Foreign Exchange market in India has become extremely dynamic, post the shift to managed float from a basket peg in the 1990s. The present study therefore attempts to estimate a multivariate GARCH model involving exchange rates of the Indian rupee vis a vis four prominent foreign currencies. Through the Dynamic Conditional Correlations (DCC) derived from the Multivariate GARCH model, a measure of the spillover of volatility across these exchange rates is attempted. The results of empirical estimation depict the prevalence of very high level of volatility and volatility clustering in each of these exchange rates. So also the volatility spillover interpreted from the behavior of the DCCs amongst these rates, is evident and asymmetric over a period of time. As a result only short term policy actions can be framed using these DCC.

Keywords: Exchange rates, Volatility, Multivariate GARCH models, Dynamic Conditional Correlations

JEL Classification: C 32 G15

1. Introduction

In the post 1990s India gradually moved from a basket peg to managed float for determining its exchange rates. This imparted greater dynamism into this segment of the financial markets, despite active intervention by the RBI. As a further policy measure, futures trading was introduced for the rupee vs dollar exchange rates in 2008, which was extended to all exchange rates in 2010. However, since exchange rates are determined by market forces randomness in returns is the natural outcome. Such randomness in returns is called as volatility or returns with hetereroskedistic variance. The volatility may persists over a period of time (ie high returns are followed by higher returns and low returns are followed by lower returns), giving rise to volatility clustering and may spread from one market to another or one financial market price to another resulting in what is called as volatility spillover. Since the volatility cannot remain constant over a period of time a theory of dynamic volatility is needed, and this gap is filled by Auto Regressive Conditional Heteroskedasticity (ARCH) models and their different variants (Engle 2003). In fact these variants of ARCH/GARCH models have become common tools for volatility related studies.

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Since Foreign Exchange Rate (FER) has a distinct impact on a number of macroeconomic variables, the knowledge of the nature and impact of volatility is very important to policy makers. So also this knowledge helps the traders in Foreign Exchange Market (FEM) to gauge the extent of risk exposure of their investments. The present study therefore estimates a multivariate Dynamic Conditional Correlations model in a multivariate GARCH framework, to study the volatility spillover, among the exchange rate of the Indian rupee vis-a-vis select hot currencies (ie. INR vs the US $, INR vs the British £, INR vs the € , and INR vs the Japanese ¥). In the process we also derive the volatilities and volatility clustering of these exchange rates vis-à-vis the Indian Rupee. The rest of the paper is organised as follows. Section II reviews the literature, in Section III explains the methodology. The results of empirical estimation are included in Section IV and the economic interpretation of the results ia given in section V. Finally Section VI Concludes.

2. Review of Literature

Multivariate GARCH models are used in multi asset volatility models. They are specially useful in studying volatility spillovers. Developments in the multivariate GARCH models were driven by the urge to reduce computational requirements, at the same time ensuring that the covariance matrices remain positive definite through suitable parameter restrictions (Bautista, 2003). Bollerslev, Engle and Wooldrige (1988), originally proposed a Multivariate GARCH (MVGARCH) model in the half vech form. This was a constant conditional correlations MV GARCH specification, where in univariate GARCH models are estimated and then the constant correlation matrix is estimated using a standard close form Maximum Likelihood Estimator correlation estimator. The constant correlations of Bollerslev were replaced by the work of Tsui and Yu, (1999), who found that constant correlations can be rejected in certain cases of assets. The BEKK formulation of Engle and Kroner (1995), factor GARCH model of Engle, Ng and Rothschild (1990), Alexander (2000) etc were distinct modifications and upgradations to the original MV GARCH model. Engle (2001), proposed a new class of estimator that both preserves the ease of estimation of Bollerslev’s conditional correlations and yet allows for non constant correlations, This Dynamic Conditional Correlations (DCC) model preserves the parsimony of univariate GARCH models of individual assets volatility with simple GARCH like time varying correlations (Engle and Sheppard, 2001). Further extensions to Engle’s DCC model can be found in Kearney & Poti (2003), Pelagatti & Roudena (2004), Lee, Shiou & Lin (2006) Billio, Caporin & Gobbo (2003, 2006) etc.

The DCC models have been extensively used to model co-movements and correlations of currencies. The relation between several European currencies and the euro have been analysed by Dijt, Munandar and Hafner (2005). Hautschand and Inkman (2003) used the DCC model to find the optimum hedge ratio of currency exchange risk exposure. Interest rate and exchange rate dynamics in Philippines was analysed using DCC model by Baurista, (2003). Qayyum and Kemal. (2006), studied the volatility spillover between the stock market and FEM of Pakistan using EGARCH model. Ching ChunWei, (2008), analysed volatility spillover across select foreign exchange rates to the stock market of Taiwan. Beine, Laurent & Lecourt (2003), studied the impact of central bank intervention on the volatility of yen vs euro.

Badrinath and Apte (2005), studied the volatility spill over across the stock market, call money market and the FEM of India using multivariate EGARCH model. The study found asymmetric volatility spillover across these marketsThe returns in the FEM is mean reverting. Mishra and Paul (2008) employed a VAR model to study the integration of the FEM and stock market of India. The study revealed that there was spillover of information from stock market to the FEM. Mishra, Swain and Malhotra (2007), studied the spillover between the FEM and stock market of India using EGARCH model. Bidirectional volatility spillover was found to exist between the two markets.

3. The Empirical Design

3.1 Multivariate GARCH Model

With increasing integration of financial markets problems like co-movements of assets, volatility spillover, contagion etc, emerge as byproducts. Since these problems are multivariate in nature the univariate ARCH and GARCH models turned out to be insufficient in explaining them. This necessitated the developments of the study of GARCH models in a multivariate framework. The multivariate GARCH model simultaneously models conditional variances (volatilities) and conditional correlations of several series. This is done in two steps:-

(1) Estimation of the Univariate GARCH models of each asset.

Suppose we have a k-vector of foreign exchange rates r_t, such that

$$r_t/\Phi_{t-1} \backsim N(0,H_t) \qquad \text{... (1)}$$

Each element of the k-vector of the foreign exchange rates used in the present study is modeled as follows:-

$$r_{it}=\mu+u_{it} \qquad \text{... (2)}$$

From the residuals of equation (2), the conditional variances of each foreign exchange rate is derived using the equation (3) given below.

$$h^2_{it}=\omega_i+\Sigma\alpha_{pi}u^2_{it}+\Sigma\beta_{qi}h^2_{it-q} \qquad \text{... (3)}$$

Where $\Sigma\alpha_{pi} + \Sigma\beta_{qi} < 0$

(2) Estimation of the Dynamic Conditional Covariance of the vector r_t

Literature shows that a number of different models on Multivariate GARCH modeling exist. These models differ with respect to the way the dynamic conditional covariance matrix H_t of r_t is modeled. The important features of some of the models are outlined in table no. 1 below and their respective methods of estimating H_t are briefly outlined through equation 4 to 8. Since the present study uses the model of Dynamic Conditional Correlations, this method has been elaborately explained.

3.1.1 The VEC model

$$Vec(H_t)=c+\sum_{j=1}^{q} A_j vech\left(r_{t-j}r'\right)+\sum_{j=1}^{p} B_J vech\left(H_{t-j}\right) \qquad \text{… (4)}$$

Where vech(.) stacks the columns of the lower triangular part of the square matrix, c is a N)N+1)/2x1 vector and Aj and Bj are N(N+1)/2xN(N+1)/2 parameter matrices.

Table 1.

Name	*Proposed By*	*Advantages*	*Disadvantage*
VEC model	Bollerslev, Engle and Wooldridge, [1988]	Flexible	The number of parameters to be estimated becomes very large. A number of restrictions are induced to make the Ht positive definite.
DVEC model	Bollerslev, Engle and Wooldridge, [1988]	No. of parameters to be estimated falls drastically	Less flexible. Lack of transmission effect
Factor Model	Engle, Ng and Rothschild [1990]	The model is very useful when the number of factors relative to the dimension of returns is small	The factors are generally correlated, which is not desired.
BEKK model	Engle and Kroner [1995]	The structure automatically provides positive definiteness to Ht	Parameter k ensures the generality of the model however when K > 1 then identification problems arise . The number of parameters to be estimated is still large
O-GARCH model	Alexander [2000]	Estimation is very easy	Identification problem arises. If the number of components m is less than N then rank of the conditional variance matrix is reduced which can be a problem for some diagnostic tests
CCC	Bollerslev [1990].	It is one of the simplest multivariate correlations model.	The correlations are assumed to be time invariant.

3.1.2 The Factor Model

$$Ht=\Omega+\sum_{k}^{K} w_k w_k^{'} f_{k,t} \qquad \dots (5)$$

Where Ω is an NxN positive semi-definite matrix, w_k, k=1,2,3….K are linearly independent Nx1 vectors of factor weights and the $f_{k,t}$, are the factors. The factor can be derived as:

$$f_{k,t}= w_k+\alpha_k(\gamma_k^{'} r_{t-1})^2+\beta_k f_{k,t-1} \qquad \dots (5.1)$$

3.1.3 The BEKK Model

$$H_t=CC^{'}+\sum_{j=1}^{q}\sum_{k=1}^{K} A_{kj}^{'} r_{t-j} r_{t-j}^{'} A_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{K} B_{kj}^{'} H_{t-j} B_{kj} \qquad \dots (6)$$

where A_{kj}, B_{kj} and C are NxN parameter matrices and C is lower triangular matrix

3.1.4 The O GARCH model

$H_t=V^{1/2}V_tV^{1/2}=V^{1/2}W_m\Sigma_tW_m^{'}V^{1/2}$ … (7)

W_m is the orthogonal N x m matrix

$W_m=P_m\Lambda_m^{1/2}$ ... (7.1)

Λ_m=diagonal(λ_1,…..λ_m) where $\lambda_1\geq$…..$\geq\lambda_m$>0 and λ is the eigenvalue of the population correlation matrix of *ut*

Pm is N x m matrix of corresponding eigenvectors to eigenvalues of the population correlation matrix of *ut a*nd V_t is the conditional variance matrix of u_t given as:

$V_{t=Var(u_{t/F_{t-1}})=W_m\Sigma_tW_m^{'}}$ ... (7.2)

3.1.5 The CCC model

$H_t=D_tPD_t$ ... (8)

where D_t is the diagonal matrix with elements D_t = diag ($h_{1t}^{1/2}$…………$h_{Nt}^{\frac{1}{2}}$) and P = [ρ_{ij}] , where the ρ_{ij}s are constant correlations.

3.2 The Dynamic Conditional Correlations (DCC) model

Engle's (2002), k-vector of assets is conditionally multivariate normal as given in equation (1).

$r_t/\Phi_{t-1}\backsim N(0,H_t)$ ... (1)

$H_t=D_tR_tD_t$ ... (9)

where

1. H_t is the Conditional Covariance matrix of r_t
2. D_t is the k x k diagonal matrix of time varying standard deviations obtained from the univariate GARCH specifications given in equation (3)
3. R_t is the k x k time varying correlations matrix. It is derived by first standardizing the residuals of the mean equation (2) of the univariate GARCH model with their conditional standard deviations derived from equation (3) to derive η_{it}. Thus

$\eta_{it} = u_{it}/\sqrt{h_{it}^2}$ … (10)

These standardized residuals are then used to estimate the parameters of conditional correlation as given in equation (11) below.

$R_t=(diag(Q_t))^{-1/2}Q_t((diag(Q_t))^{-1/2}$ ... (12)

and

$Q_t=(1-\alpha_i-\beta_i)\bar{Q}+\alpha_i\eta_{it-1}\eta'_{it-1}+\beta_iQ_{t-1}$ ... (13)

where $\bar{Q}$ is the unconditional covariance of the standardized residuals. The Q_t does not generally have ones on the diagonal, so it is scaled as equation (12) above, to derive R_t, which is a positive definite matrix. In this model the conditional correlations are thus dynamic or time varying. The model was further modified by Pesaran & Pesaran (2007), to accommodate multivariate t distribution of returns.

3.3 Data Description

Daily data on the exchange rates of the INR with the US $, British £, European € and Japanese ¥, was collected for the period 5-4-2010 to 18-7-2011, from the RBI Handbook of Statistics. The data was subdivided into four subperiods in order to highlight the dynamic nature of volatility and the Dynamic Conditional Correlations. As a result separate estimations of the DCC for each of these sub periods (comprising an N equal to 80 observations) were carried out. The empirical analysis has the following steps:-

1. Descriptive statistics of all the variables for all the sub periods.
2. Stationarity test of all the data using Augmented Dicky fuller[1] (ADF) test and Phillips Peron (PP)[2] test.
3. Estimation of ARIMA[3] model of all the exchange rates, for conducting LM test to identify possible ARCH effects.
4. Estimate the Multivariate GARCH model.
5. Graphical representation of all the conditional variances which represent the volatilities of the exchange rates under study.
6. Graphical representation of the Dynamic Conditional Correlations (DCC) derived from the MV GARCH model, to show the volatility spillover for all the sub periods.

4. Results of Empirical Analysis

Step I

The descriptive statistics of the data sub sample wise, has been reported in Tables 2, 3 4 and 5 given below. From these tables the following conclusions about the data can be derived:-

1. Since none of the data has a skewness equal to 0 and kurtosis equal to 3, none of the exchange rates is distributed normally. This conclusion is further supported for all the exchange rates in the different sub periods, by the JB statistics, which rejects normal distribution.
2. A detail study of the variances highlights a few important things. Traditionally the standard deviations (square routes of variances) are used as indicators of volatility in the data. A closer look of the same shows that the volatility of the $ exchange rate has been gradually falling, while that of the pound has been having alternating phases of high and low volatility (variances). The euro exchange rate behaves like the US $ while the yen seems to exhibiting a wave like pattern.

Step II

The ADF test and PP test for stationarity revealed that all the exchange rates were non stationary in level form, but became stationary after first differencing (result not reported). As a result all the data was used in first difference.

Table 2. Descriptive statistics for the sample 5/4/10 to 26/7/10

	Dollar	*Pound*	*Euro*	*Yen*
MEAN	45.95184	68.80016	58.36309	50.48057
MODE	44.455	68.3388	61	47.385
MEDIAN	46.44	68.3813	58.4	50.8125
STD	1.0455	1.620562	1.432164	2.315656
VAR	1.093071	2.626223	2.051095	5.362263
SKEW	-0.36648	0.595032	0.169118	-0.01812
KURT	-1.47036	-0.08936	-1.18813	-1.30214
JB Stat	68.3873952	36.526	58.835	61.684

Table 3. Descriptive statistics for the sample 27/7/10 to 19/11/10

	Dollar	*Pound*	*Euro*	*Yen*
MEAN	45.55105	71.71337	60.99989	54.40646
MODE	46.575	71.134	61.0265	53.702
MEDIAN	45.605	71.62125	60.8014	54.496
STD	1.029561	1.057553	1.840399	0.745163
VAR	1.059997	1.118419	3.387068	0.555268
SKEW	-0.04059	0.049362	5.638419	0.107466
KURT	-1.72583	-1.00176	42.55131	-0.97701
JB Stat	74.448	53.399	5636.8	52.863

Table 4. Descriptive statistics for the sample 22-11-10 to 16-3-11

	Dollar	Pound	Euro	Yen
MEAN	45.32666	71.91634	61.05025	54.74494
MODE	45.16	71.4238	#N/A	54.9725
MEDIAN	45.305	72.54775	61.28755	54.69315
STD	0.281911	1.351631	1.337482	0.572221
VAR	0.079474	1.826907	1.879861	0.327437
SKEW	0.169324	-0.48471	-0.08934	0.360336
KURT	-0.33629	-1.13089	-1.41736	-0.40386
JB Stat	37.47567	59.998	65.134	40.342

Table 5. Descriptive statistics for the sample 17-3-11 to 18-7-11

	Dollar	Pound	Euro	Yen
MEAN	44.73147	72.73369	64.21929	54.97538
MODE	44.685	71.9135	#N/A	55.33
MEDIAN	44.735	72.87125	64.26825	55.29505
STD	0.300139	0.86383	0.824282	1.044619
VAR	0.090083	0.746202	0.679441	1.09123
SKEW	-0.06161	-0.35146	0.288031	-1.48605
KURT	-0.65322	-0.49803	-0.24098	2.242397
JB Stat	44.526	42.424	36.11	31.35

Step III

Autoregressive Integrated Moving Average (ARIMA) models of each of these exchange rates were conducted. The residuals of each of these ARIMA models were tested for ARCH effects using the ARCH-LM test for the all the variables during all the sub periods. Significant ARCH effects were found for the entire data set (results not reported).

Step IV and Step V

The multivariate GARCH model and the DCC were then estimated separately for each of the sub periods. The model was highly significant. Results reported in appendix I. The conditional volatilities (following equation 3 above) and the DCCs in a multivariate framework were obtained for each of the exchange rates. The figures 1, 2, 3 and 4 graphically represent a comparison of the (conditional variances) volatilities of all the four exchange rates in the four sub samples respectively. At this stage it is important to note that the entire sample covers a period when UK had just recovered from a very severe recession. So was the case with Japan, which was recovering from the economic crisis of 2009 when it suffered one of the most severe earth quake towards the end of the third sample. The euro was reeling under the most severe crisis throughout the sample period and the US was gradually recovering amidst global fears of a double dip depression.

From the figures 1, 2, 3 and 4 below, the following observations can be made. During the first sample period all the exchange rates are extremely volatile. After reaching a peak the volatilities are falling. Of all the exchange rates the yen is the most volatile and the dollar the least. Some synchronization is also evident between the yen, the euro and the pound. Volatility clustering is very clear in all the exchange rates.

During the second sample period the magnitude of volatility is more or less constant for all the exchange rates except the euro which had a very high volatility initially. This may probably due to the European crisis which was peaking during this phase. Volatility clustering is again very evident for all exchange rates.

The third sample shows an extremely steady volatility in case of all the exchange rates under consideration, throughout the sample period. During this phase Euro continues to be the most volatile and the dollar the least. All the exchange rates exhibit volatility clustering.

Finally, during the fourth sample period the yen is the most volatile exchange rate, which may be due to the natural calamity that hit Japan during this period. Except for small phases, the euro and the pound have similar volatilities. Again the dollar is the least volatile. The relative stability of dollar during all the sample periods may be a reflection of the gradual economic recovery in the US.

Step VI

The Multivariate DCC of these exchange rates depict the extent of dependence or influence of volatility of one exchange rate on the other, so also it reflects the changing pattern of this dependence or influence. The DCC vary within a range of -1 to +1 with their graphs depicting umbrella like structures. The DCC reflect the extent of volatility spillover (ie transmission of volatility from one exchange rate to another) among the exchange rates. When the DCC is positive there is a direct relation among the exchange rates' volatilities (ie increase in volatility one exchange rate leads to increase in volatility of the other exchange rate). Where as a negative DCC implies that the exchange rates' volatilities move in the opposite directions (ie increase in volatility of one exchange rate leads to a decrease in volatility of the other). The table no. 6 below summarizes the DCCs which were derived from the MV-GARCH model. The validity of the MV-GARCH model was then tested using the LM test for serial correlation[4] of the probability integral transforms[5], and was found significant

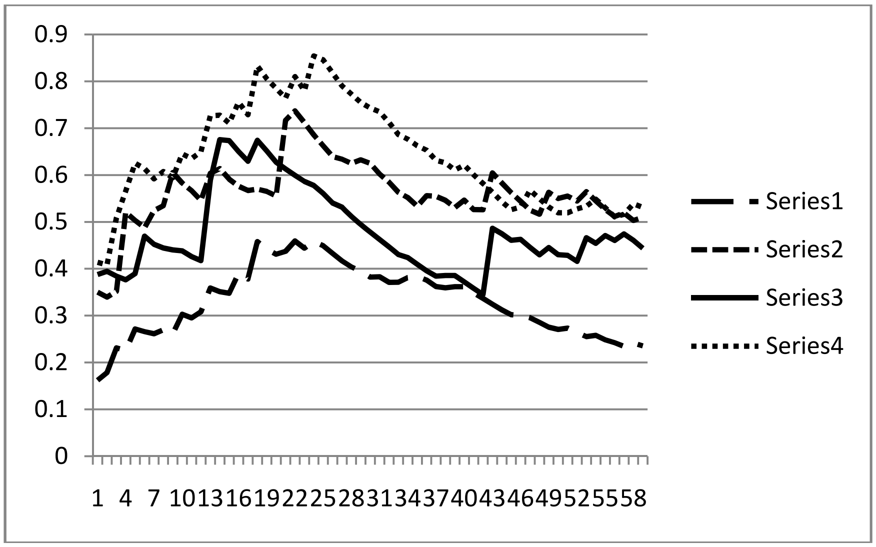


Figure 1. Volatilities of All the Exchange Rates for The Sample Period: 4-4-10 to 26-7-10

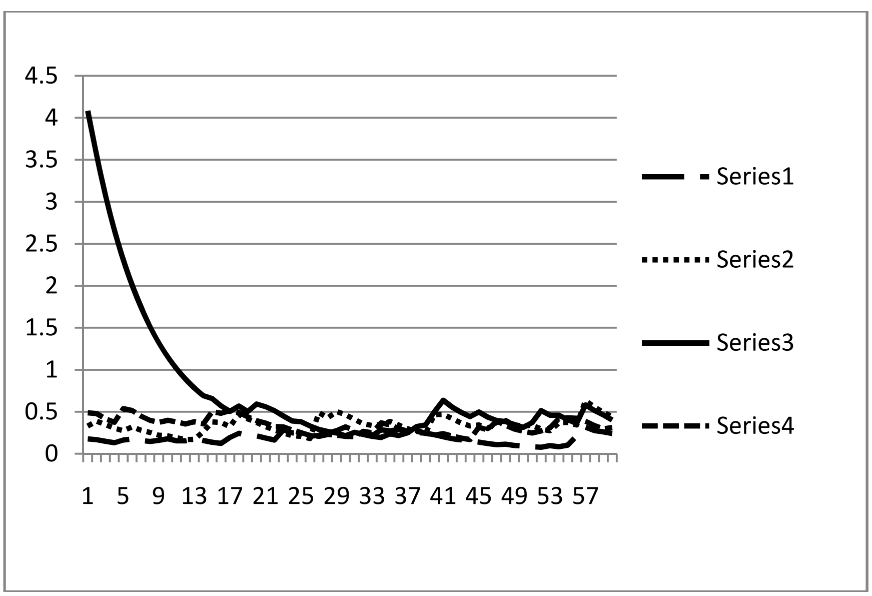


Figure 2. Volatilities of All the Exchange Rates for the Sample Period : 27-7-10 to 19-11-10

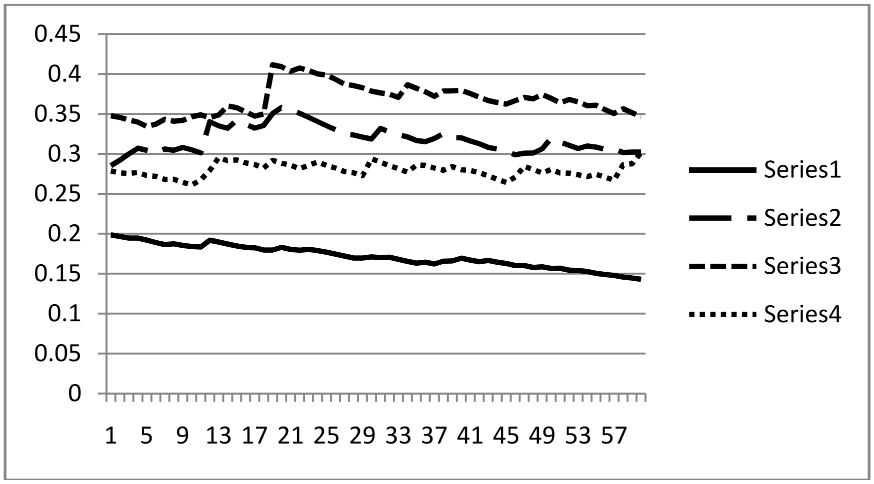


Figure 3. Volatilities of All the Exchange Rates for the Sample Period : 22-11-10 to 16-3-11

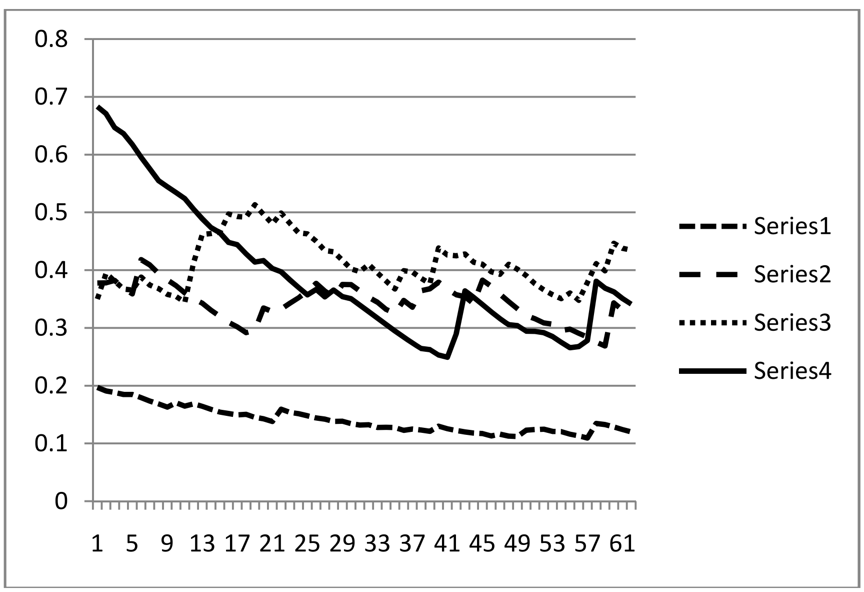


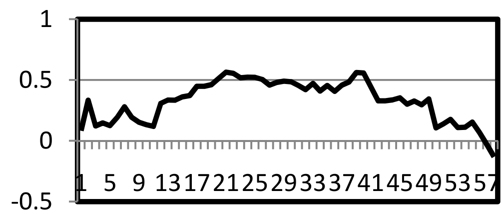
Figure 4. Volatilities of All the Exchange Rates for the Sample Period : 18-3-11 to 18-7-11

Note: for all figures:

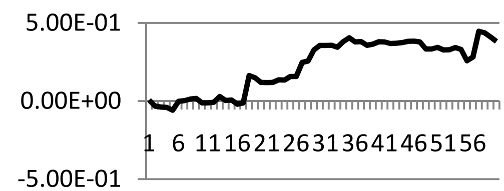
(1) series 1 is \$ vs Re exchange rate; (2) Series 2 is £ vs Re exchange rate

(3) Series 3 is € vs Re exchange rate; (4) Series 4 is ¥ vs Re exchange rate

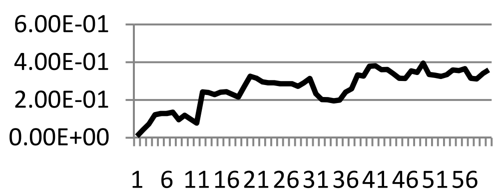
5. Dynamic Conditional Correlation between £ and $ (5-4-10 to 26-7-10)



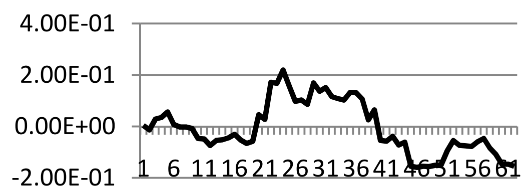
6. Dynamic Conditional Correlation between £ and $ 27-7-10 to 19-11-10)



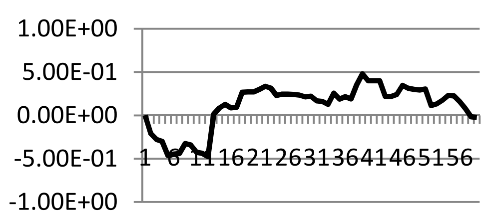
7. Dynamic Conditional Correlation between £ and $ (22-11-10 to 16-3-11



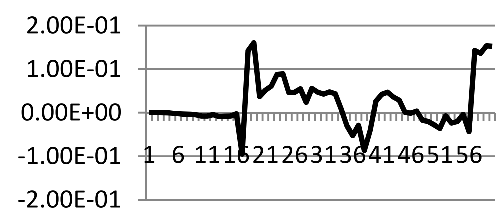
8. Dynamic Conditional Correlation between £ and $ 18-3-11 to 18-7-11



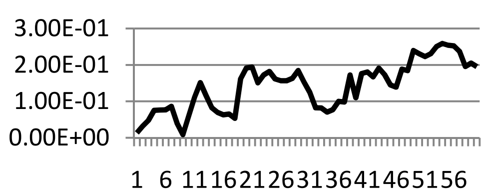
9. Dynamic Conditional Correlation between € and $ 5-4-10 to 26-7-10



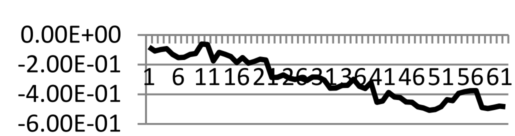
10. Dynamic Conditional Correlation between € and $ 27-7-10 to 19-11-10



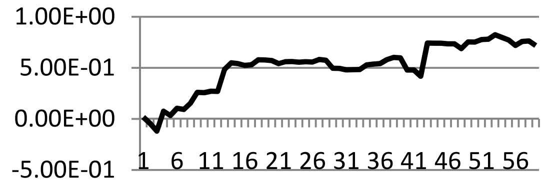
11. Dynamic Conditional Correlation between € and $ 22-11-10 to 16-3-11



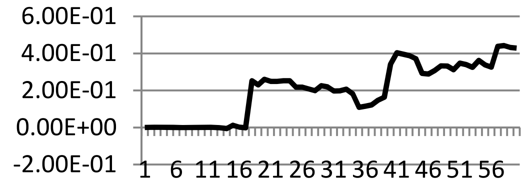
12. Dynamic Conditional Correlation between € and $ 18-3-11 to 18-7-11



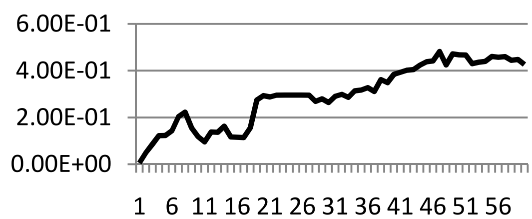
13. Dynamic Conditional Correlation between € and £ 5-4-10 to 26-7-10



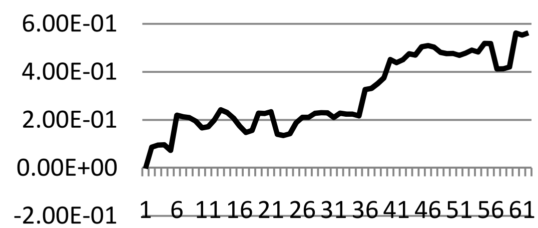
14. Dynamic Conditional Correlation between € and £ 27-7-10 to 19-11-10



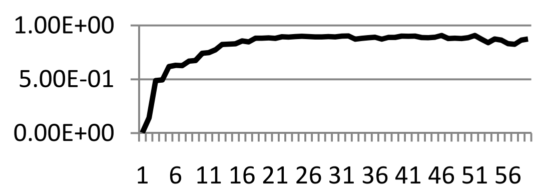
15. Dynamic Conditional Correlation between € and £ 22-11-10 to 16-3-11



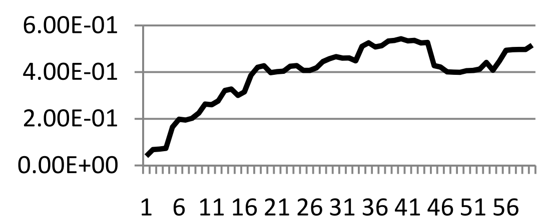
16. Dynamic Conditional Correlation between € and £ 18-3-11 to 18-7-11



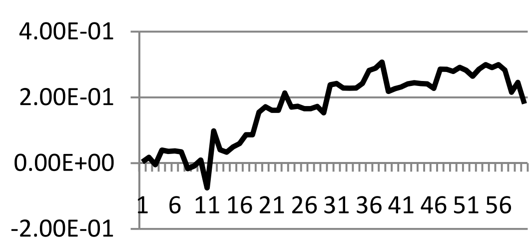
17. Dynamic Conditional Correlation between ¥ and $ 5-4-10 to 26-7-10



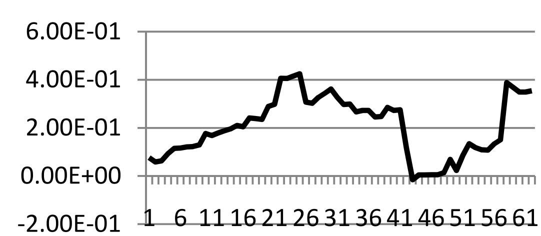
18. Dynamic Conditional Correlation between ¥ and $ 27-7-10 to 19-11-10

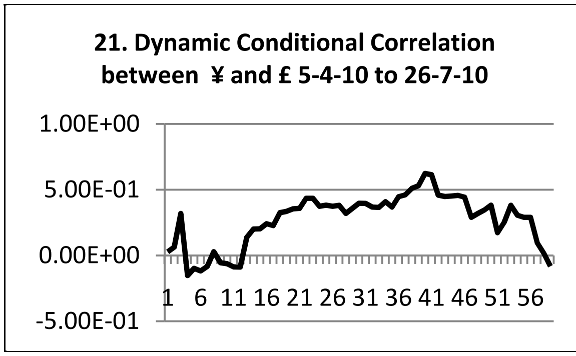


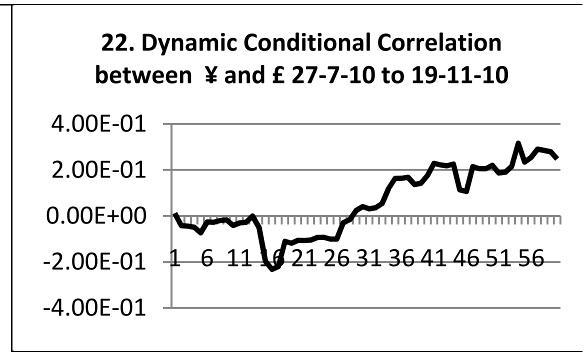
19. Dynamic Conditional Correlation between ¥ and $ 22-11-10 to 16-3-11

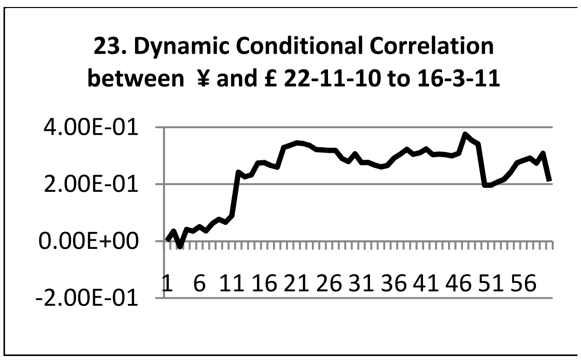


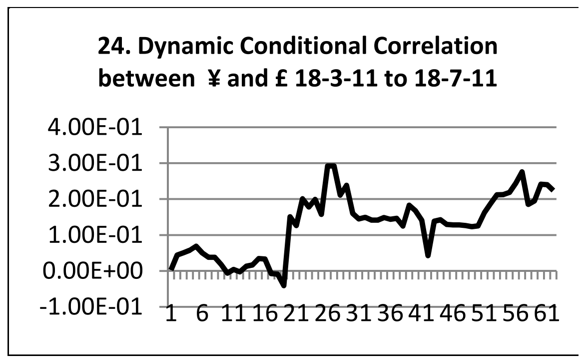
20 Dynamic Conditional Correlation between ¥ and $ 18-3-11 to 18-7-11

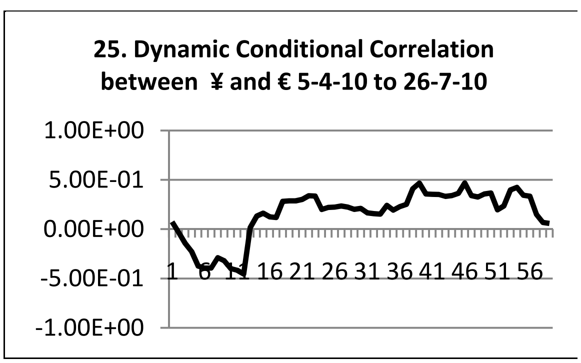


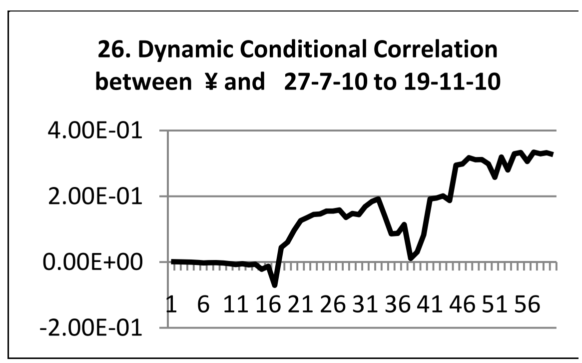

21. Dynamic Conditional Correlation
between ¥ and £ 5-4-10 to 26-7-10
1.00E+00
5.00E-01
0.00E+00
-5.00E-01
1 6 11 16 21 26 31 36 41 46 51 56

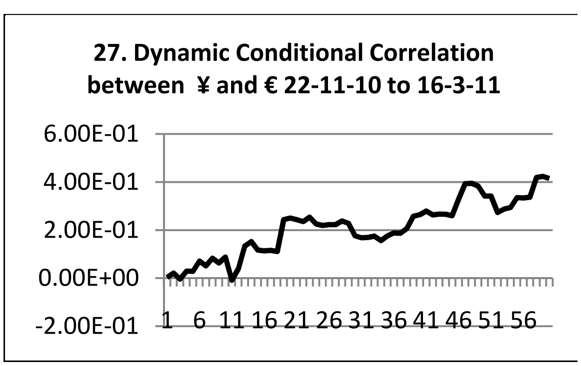

22. Dynamic Conditional Correlation
between ¥ and £ 27-7-10 to 19-11-10
4.00E-01
2.00E-01
0.00E+00
-2.00E-01
-4.00E-01
1 6 11 16 21 26 31 36 41 46 51 56


23. Dynamic Conditional Correlation
between ¥ and £ 22-11-10 to 16-3-11
4.00E-01
2.00E-01
0.00E+00
-2.00E-01
1 6 11 16 21 26 31 36 41 46 51 56


24. Dynamic Conditional Correlation
between ¥ and £ 18-3-11 to 18-7-11
4.00E-01
3.00E-01
2.00E-01
1.00E-01
0.00E+00
-1.00E-01
1 6 11 16 21 26 31 36 41 46 51 56 61


25. Dynamic Conditional Correlation
between ¥ and € 5-4-10 to 26-7-10
1.00E+00
5.00E-01
0.00E+00
-5.00E-01
-1.00E+00
1 6 11 16 21 26 31 36 41 46 51 56


26. Dynamic Conditional Correlation
between ¥ and 27-7-10 to 19-11-10
4.00E-01
2.00E-01
0.00E+00
-2.00E-01
1 6 11 16 21 26 31 36 41 46 51 56


27. Dynamic Conditional Correlation
between ¥ and € 22-11-10 to 16-3-11
6.00E-01
4.00E-01
2.00E-01
0.00E+00
-2.00E-01
1 6 11 16 21 26 31 36 41 46 51 56

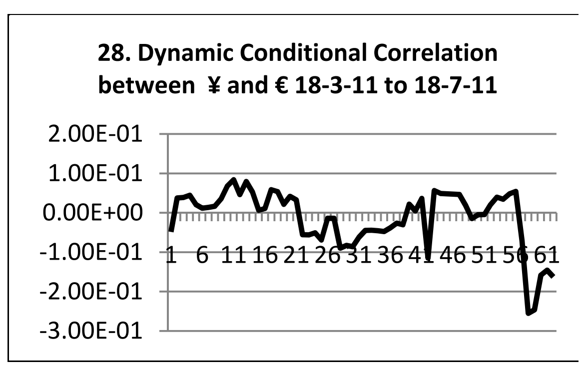

28. Dynamic Conditional Correlation
between ¥ and € 18-3-11 to 18-7-11
2.00E-01
1.00E-01
0.00E+00
-1.00E-01
-2.00E-01
-3.00E-01
1 6 11 16 21 26 31 36 41 46 51 56 61

Table 6. Summary of Dynamic Conditional Correlations (DCC's) derived from the multivariate GARCH model

DCC *Sample Period*	*£ and $*	*€ and $*	*€ and £*	*¥ and $*	*¥ and £*	*¥ and €*
4-4-10 to 26-7-10	- magnitude of DCC is very high - positive	-DCC negative in the beginning, becomes positive later -magnitude of is very low	-gradually increasing DCC -positive through out -magnitude very low	- near constant DCC -magnitude relatively high	-alternate phases of negative and positive DCC in the beginning -magnitude very low	-initial negative DCC followed by positive DCC -becomes positive -magnitude very low
27-7-10 to 19-11-10	-falls drastically -gradually picks up -majorly positive DCC	-alternate phases of positive and negative DCC -magnitude continues to be very small	-zero DCC for a considerable period -gradually increases positively	-gradually increasing DCC -magnitude less than the earlier period	-long phases of zero and negative DCC -becomes positive -magnitude increasing but marginal	-near zero DCC for a long time -spiky rise thereafter -magnitude very low
22-11-10 to 16-3-11	-steady growth -DCC marginal (range 0.00E to 5.00E-01) -positive	-DCC becomes positive through out -magnitude is still very small	-positive and rising -magnitude sill very low	-increasing DCC -magnitude still lower than before	-positive throughout -increase in DCC -magnitude still marginal	-steadily rising -positive through out -magnitude very low
18-3-11 to 18-7-11	-fluctuating -alternate phases of positive and negative DCC	-DCC is negative through out -magnitude goes on increasing	-same as above	-fluctuations in DCC -positive but marginal magnitude	-spiky DCC -extremely low magnitude initially, picks up later -positive through out	-alternate phases of positive and negative DCC -magnitude very low

5. Economic Interpretation of The Empirical Results

The following economic interpretations about the empirical results can be made

1) The DCC are asymmetric, hence volatility spillover is unpredictable.

The data was divided into 4 subperiods to highlight the fact that the DCCs between the same set of FER are asymmetric. This has emerged very clearly in the estimated DCCs. This clearly implies that policy makers cannot predict volatility spillovers on the basis of the past. The

DCCs can serve as very crucial input in the short run for policy makers during an ongoing financial or economic crisis.

2) DCC can be used for short term portfolio selection

The results show negative DCC during a number of subperiods. Which can serve as very useful signals for portfolio switching. A volatile currency can be replaced by its negative DCC counterpart by traders in foreign exchange market. Similarly exporters and importers can select their markets based on the DCC during volatile conditions.

3) The magnitude of DCC tells the extent of spillover

Throughout the estimation period the magnitude of DCC among the exchange rates has been megre. This implies that the magnitude of volatility spillover in the foreign exchange market of India is still very small.

4) A closed capital account can be a long term solution to the problem of volatility spillover

The asymmetric DCC between a set of FERs over time also rekindles the glory of a closed capital account. Opening up of the capital account means opening it up to these unpredictable correlations.

6. Conclusions

From the results of empirical estimation for volatility of the exchange rates under consideration, it is clear that all the exchange rates are extremely volatile in nature. However, throughout the study period, the volatility of dollar exchange rate is very low. The Euro volatility was very high during two phases, and that of the yen was very high during one phase. Volatility clustering is clearly evident in all the phases and among all the exchange rates.

The extent of volatility depends on the domestic economic conditions of the parent country of the currency. The relatively lower volatility of dollar may be due to the economic recovery in the US, so also due to the existence of future trading in this currency in India.

Volatility spillover among these exchange rates is also evident. However, the extent of spillover is very less. So also the direction (ie negative or positive) of spillover is also variable. This imparts considerable uncertainty to the prediction of volatility spillovers. However, given the meager magnitude of the DCCs the extent of volatility spillover doesn’t seem to be a very big problem in the foreign exchange market of India. Policy intervention of short term nature can help.

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Appendix I

Multivariate GARCH with underlying multivariate t-distribution
Converged after 32 iterations (1st sample period)

Based on 58 observations from 22 to 79.

The variables (asset returns) in the multivariate GARCH model are:

x5 x6 x7 x8

Volatility decay factors restricted to add up to 1, same for all variables.

Correlation decay factors restricted to add up to 1, same for all variables.

Devolatized Returns based on 20-Period Rolling Historical Volatilities

Parameter	Estimate	Standard Error	T-Ratio[Prob]
lambda	.92715	.030216	30.6839[.000]
delta	.89986	.018641	48.2738[.000]
df	7.2190	2.0342	3.5489[.001]

Maximized Log-Likelihood = -124.2027

df is the degrees of freedom of the multivariate t distribution

Multivariate GARCH with underlying multivariate t-distribution
Converged after 26 iterations (2nd Sample period)

Based on 59 observations from 22 to 80.

The variables (asset returns) in the multivariate GARCH model are:

x5 x6 x7 x8

Volatility decay factors restricted to add up to 1, same for all variables.

Correlation decay factors restricted to add up to 1, same for all variables.

Devolatized Returns based on 20-Period Rolling Historical Volatilities

Parameter	Estimate	Standard Error	T-Ratio[Prob]
lambda	.75210	.042024	17.8966[.000]
delta	.96127	.013295	72.3008[.000]
df	5.3708	1.3318	4.0328[.000]

Maximized Log-Likelihood = -73.7540

df is the degrees of freedom of the multivariate t distribution

Multivariate GARCH with underlying multivariate t-distribution
Converged after 26 iterations (3rd Sample period)

Based on 59 observations from 22 to 80.
The variables (asset returns) in the multivariate GARCH model are:
x5 x6 x7 x8
Volatility decay factors restricted to add up to 1, same for all variables.
Correlation decay factors restricted to add up to 1, same for all variables.
Devolatized Returns based on 20-Period Rolling Historical Volatilities

Parameter	Estimate	Standard Error	T-Ratio[Prob]
lambda	.96974	.021381	45.3560[.000]
delta	.96367	.013577	70.9761[.000]
df	18.5790	15.5701	1.1932[.238]

Maximized Log-Likelihood = -14.1183 (The sample was also estimated using normal distribution. But the Loglikelihood function is bigger in case of t distribution)

df is the degrees of freedom of the multivariate t distribution

Multivariate GARCH with underlying multivariate t-distribution
Converged after 26 iterations (4th sample period)

Based on 61 observations from 22 to 82.
The variables (asset returns) in the multivariate GARCH model are:
x5 x6 x7 x8
Volatility decay factors restricted to add up to 1, same for all variables.
Correlation decay factors restricted to add up to 1, same for all variables.
Devolatized Returns based on 20-Period Rolling Historical Volatilities

Parameter	Estimate	Standard Error	T-Ratio[Prob]
lambda	.92893	.020381	45.5784[.000]
delta	.95217	.016285	58.4676[.000]
df	8.0783	3.3268	2.4283[.018]

Maximized Log-Likelihood = -22.8230
df is the degrees of freedom of the multivariate t distribution

End Notes

1) The Augmented Dickey-Fuller Test for stationarity

Depending upon the nature of the time series it may be represented as in the equation (1) or equation (2) or equation (3).

$$\Delta Yt=\delta Yt-1+ut \quad \ldots (1)$$

$$\Delta Yt=\beta 1+\delta Yt-1+ut \quad \ldots (2)$$

$$\Delta Yt=\beta 1+\beta 2t+\delta Yt-1+ut \quad \ldots (3)$$

The Augmented Dicky Fuller (ADF) test under the null of non stationarity can be conducted to test whether a given series is stationary or not. This test is conducted by augmenting either of the above three equations by adding the lagged value of the dependent variable ΔYt. Thus each of the above equation will be as follows:-

$$\Delta Yt=\delta Yt-1+\alpha i \ \Sigma \ \Delta Yt-I \ +et \quad \ldots(4)$$

$$\Delta Yt=\beta 1+\delta Yt-1+\alpha i \ \Sigma \ \Delta Yt-I \ +et \quad \ldots (5)$$

$$\Delta Yt=\beta 1+\beta 2t+\delta Yt-1+\alpha i \ \Sigma \ \Delta Yt-I + et \quad \ldots (6)$$

where et is a pure white noise error, and the number of lagged difference term to include is determined empirically (Gujarati, 2005). In each of the above equations if $\delta=0$ the series is non stationary. The Dicky Fuller tables can be used to test the significance of the hypothesis.

2) The Phillips-Perron Test (PP) for stationarity

It uses non parametric statistical methods to take care of the serial correlation in the error terms instead of adding lagged difference terms.

3) ARIMA Model

A process that combines Autoregressive process (AR) and Moving Average terms (MA) terms. I stands for the order of integration (ie the number of times the data has to be differenced to make it stationary). AR process where the present observations depend on the previous observations and MA is a weighted average of the present and the recent past observations of a process. Such models are estimated using the Box-Jenkins (1976) methodology.

4) LM test for Serial Correlation on probability integral transform variables

Under the null hypothesis of correct specification of the t DCC model the probability integral transform variables are serially uncorrelated and uniformly distributed over the range (0,1). Here the LM statistics has to be insignificant.

5) Probability integral transform variables

The probability integral transform or transformation relates to the result that data values that are modeled as being random variables from any given continuous distribution can be converted to random variables having a uniform distribution. This holds exactly provided that the distribution being used is the true distribution of the random variables.

6) Kolmogorov-Smirnov Test

Test for the uniform distribution of the probability integral transform variables, under the null of uniform distribution.

♦♦♦