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CO-MOVEMENTS AND VOLATILITY SPILLOVER IN ASIAN FOREX MARKET: A MULTIVARIATE GARCH AND MRA APPROACH

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Abstract

This paper makes an effort to analyze the co-movements and integration of selected Asian foreign exchange markets using both the time series and time-frequency approaches. The correlation structure between forex markets, and the time domain information on varying correlations, is captured using the multivariate dynamic conditional correlation GARCH method whereas the time-horizon specific information on the dynamics of correlation is captured using methods from wavelet analysis. The results from time domain volatility models reveal significant volatility transmission between most of the countries. On the other hand, the use of time-scale methods from the wavelet domain, makes it possible to detect the correlation dynamics in varying time horizons, which has revealed the existence of a strong correlation between all the seven markets with evidence of a nearly perfect integration of markets in the long run time horizon.

Key words: Exchange Rates, Dynamic Conditional Correlation, Multiresolution Analysis, Wavelet Multiple Cross Correlation

JEL Codes: C32, G15

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1. INTRODUCTION:

Integraion of the financial market has become a debatable topic during past couple of decades across the world. Rapid growth of capital flows between countries, promotion of export led growth with limited trade barriers and adoption of a freely floating exchange rates has made global markets more integrated. The contagious effect of the east Asian crisis led to the concentration of some research on the integration of east Asian economies. Economic debacle of forex market, which spread across Asian countries, have great influence in shifting the foreign excahnge regimes and policies. A shift from fixed exchange rate regime to managed/float exchange rate regime will always open the door for more integration of forex market and strengthen the relationship of the market between the countries.

The focus of this study is to analyse the interlinkages between some Asian forex markets by using DCC – GARCH method, which helps in uncovering the dynamic correlation structure between markets and time scale approach of wavelets which incorporates information from varying time horizons helping one to characterize the interdependencies in short, medium and long run time horizon of interest.

2. LITERATURE REVIEW:

The introduction of ARCH model by Engel (1982) helped overcome the limitation of classical linear regression models which assume homoscedastic nature of the data. Later on, wide range of methodological and analytical literature came up which took into account the heteroscedastic nature of data. Multivariate time series models that incorporated conditional heteroscedasticity with constant conditional correlation (CCC) were proposed by Bollerslev, Engle and Wooldrige (1988). Engle and Kroner (1995) proposed a BEKK[4] multivariate GARCH model by ensuring positive parameters that helped to check the spillover between the variables directly from the model. Factor GARCH models of Engle, Ng and Rothschild (1990) and Alexander (2000) were

[4] This short name BEKK comes as result of synthesized works of Baba, Engle, Kraft and Kroner (1995)

introduced as modified extensions of the original multivariate GARCH model. The restrictive assumption of constant conditional correlation, which did not explain the time varying correlations, had some limitations as it did not explain the evolution of correlation over time. This led to the development of new models by Tsui and Yu (1999) wherein the constant conditional correlation assumption was relaxed and was extended to include the dynamic evolution of correlation. The empirical evidences revealed that the constant correlations did not hold for all assets and varies over time. Engle (2002) and Tse and Tsui (2002) proposed a generalized version of the CCC model by allowing the conditional correlation to vary over time. The proposed model, known as dynamic conditional correlation (DCC) model, fits univariate GARCH models of the series and checks the conditional correlation of the standardized residuals. Kearney & Poti (2003), , Lee, Shiou & Lin (2006) and Billio, Caporin & Gobbo (2003, 2006) proposed different extended versions of the DCC model.

Conditional heteroscedastic models, in a multivariate setting, are widely used to check volatility spillover and integration of markets. This led to a rise in empirical literature, based on multivariate GARCH models, in the area of financial markets. However, works that analyzed foreign exchange markets with the help of these new multivariate GARCH models were not abundant. Diebold and Nerlove (1989), Bollerslev (1990), Engle, *et al*. (1990) were some of the main contributors who made efforts to model volatility spillover, using various forms of univariate and multivariate GARCH models, between various foreign exchange markets. Kearney and Patton (2000) used multivariate GARCH models to examine volatility transmission mechanism between the members of the European Monetary System (EMS). The study revealed significant volatility spillover among the member nations. Moreover, the transmission was found to be high for daily data series as compared to weekly data. The causal relationship of return and volatility series was also an interesting area where some authors tried to explore the phenomenon in foreign exchange markets. Hong (2001) checked the causality between US Dollar exchange rate with respect to the Deutsche Mark (DEM) and the Japanese Yen (JPY) and found simultaneous interactions between these exchange rates. While Chowdhury and Sarno (2004) employed multivariate stochastic volatility models for spillover analysis, Lee (2010) studied cross-country mean and volatility transmission between ten emerging foreign exchange markets in Asia and Latin America by using multivariate GARCH models. The results from both analyses revealed significant volatility pass through across the markets.

The possibility of common currency areas and economic unions made the study of exchange rate co-movements and spillover very popular, thereby generating plentiful economic literature encompassing exchange rate co-movements. Moreover, the introduction of euro currency also led to the production of numerous works that analyzed the dynamics between euro and other developed currencies. The efforts of Nikkinen *et al.* (2006), Perez-Rodriguez (2006), Inagaki (2007), McMillan and Speight (2010) to check the spillover of return and volatility from other major currencies, including pound, yen, us dollar and British pound to euro, revealed significant interactions and informational spillover between these exchange rates. Later on, detailed analysis of Nikkinen *et al.* (2011) using wavelet based time series methods also confirmed these results by showing that the expectations of euro, the Japanese yen, and the British pound vis-a-vis the US dollar were closely connected. The study also revealed interesting results, by capturing information from varying time horizons, which explained the short and long run relationship between these exchange rate variables. Contrary to studies that used traditional GARCH methodology, Boero *et al.* (2011), examined the bivariate dependence of the Deutsche mark, the British pound, the Swiss franc and the Japanese yen vis-`a-vis the US dollar before and after the introduction of the euro using Copula and non-parametric plots. The study revealed increase in co-movement between pound and euro during post-euro era with no significant change, even after the introduction of euro, in the co-movement of euro and franc. Antonakakis (2012) also confirmed the ETC examined the correlation structure among the Eurozone equity market by implementing wavelet multiple correlation and cross correlation method using daily data from major equity indices from Europe. Evidences for perfect co-integration among the EU equity markets were found at an annual scale. CAC 40 of France was identified as the potential leader among the markets.

There are many research papers which analyze the volatility transmission mechanism between major exchange rates across the world, however, empirical studies that examine the integration and volatility spillover between forex markets of Asia using both conditional heteroscedastic and wavelet methods are very limited. Therefore, the main focus of this paper is to augment the literature of co-movement among Forex markets of Asia by examining pair- wise transmission of volatility between major Asian forex markets and to analyze the relationship between these markets from the perspective of a non-homogenous time-frequency based approach, enabling to capture information from various time horizons of interest.

3. DATE AND METHODOLOGY:

Six Major Asian countries are selected for the study. The dataset includes monthly exchange rate per US dollar for the seven Asian countries namely, Indian Rupee, South Korean Won, Malaysian Ringgit, Singapore Dollar Japanese Yen, Indonesian Rupiah, and Chinese Yuan from February 1993 to June 2015. The dataset analyzed in the study is consists of monthly average value of exchange rates obtained from International Financial Statistics CD-ROM. Table 1 presents descriptive statistics for the corresponding return series. Sample means, medians, maximums, minimums, standard deviations, skewness, kurtosis, Jarque–Bera statistic and p-values are reported for the monthly exchange rate returns.

Table. 1 Dsicriptive Statistics of log Retruns

	Indian Rupee	South Korean Won	Malaysian Ringgit	Singapore Dollar	Japanese Yen	Indonesian Rupiah	Chinese Yuan
Mean	0.00140	0.00050	0.00060	-0.00030	0.00005	0.00301	0.00033
Std. Dev.	0.00850	0.01480	0.00950	0.00580	0.01150	0.02887	0.00040
Skewness	2.89170	5.19480	1.14310	0.28350	-0.38150	4.32403	-0.86820
Kurtosis	25.68400	54.50720	23.16840	5.99440	4.10540	45.61854	10.20220
Jarque-Bera	6142.27***	30945.49***	4617.73***	104.10***	20.22***	21196.4***	615.18***
LB-Q	18.5504*	53.1011***	28.4301***	30.6540***	27.9450***	27.6548***	33.0011***
LB-Q^2	33.0001*	26.7882*	101.560***	60.7870***	21.0970**	119.451***	61.9143***
KPSS	0.1869***	0.0800***	0.1354***	0.1495***	0.1462***	0.0539***	0.0996***

A summary review of DCC- GARCH and Wavelet methodologies are as follows:

a) Mulitvariate GARCH – DCC Model:

The purpose of this multivariate DCC GARCH model is to assess the evolution of correlations between exchange rates of seven Asian countries over a period of time. This model helps to understand and determine whether the correlation between exchange rate increases and decreases. The DCC model has several advantages compared to the simple correlation analysis. First, it is parsimonious compared to many multivariate GARCH models. Second, the DCC models are flexible since they allow for volatility of different assets to be taken into account over time. The multivariate DCC model can be represented as

$$r_t = \mu_t + \varepsilon_t, \varepsilon_t | \mathrm{I}_{t-1} \to N(0, H_t) \qquad \text{……………………..} \quad (1)$$

Where, $H_t = D_t R_t D_t$ and r_t is the $(k \times 1)$ vector of the returns on forex markets; ε_t is a $(k \times 1)$vector of zero mean return innovations conditional on the information available at time t-1. D_t is a $(k \times k)$diagonal matrix with elements on its main diagonal being the conditional standard deviations of the returns on each market in the sample and R_t is the $((k \times k))$ conditional correlation matrix. D_t and R_t are defined as follows:

$$D_t = diag(h_{11t}^{\frac{1}{2}} \dots . h_{kkt}^{\frac{1}{2}}) \qquad \text{……………………..} \quad (2)$$

Where, h_{11t} implies GARCH (1, 1) process

The correlation matrix is then given by the transformation

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}} \qquad \text{……………………..} \quad (3)$$

Where Q_t is

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \eta_{t-1} \acute{\eta}_{t-1} + \beta Q_{t-1} \qquad \text{…………….} \quad (4)$$

Where, $\eta_t = \varepsilon_{it} / \sqrt{h_{it}}$, the standardized residuals from univariate GARCH model,

$\bar{Q} = T^{-1} \sum \eta_t \acute{\eta}_t$ is an $(n \times n)$ conditional variance matrix of ε_t and α and β are non-negative scalars such that α + β < 1

The conditional correlation coefficient between the two markets i and j is then expressed by the following equation:

$$\rho_{ij} = \frac{(1-\alpha-\beta)q_{ij}+\alpha\eta_{it-1}\eta_{jt-1}+\beta q_{ij,t-1}}{((1-\alpha-\beta)\overline{q_{ii}}+\alpha\eta_{i,t-1}^2+\beta q_{ii,t-1})^{\frac{1}{2}}((1-\alpha-\beta)\overline{q_{jj}}+\alpha\eta_{j,t-1}^2+\beta q_{jj,t-1})^{1/2}} \quad \dots (5)$$

Here, q_{ij} refers to the element located in the **i'**th row and **j'**th column of the symmetric positive definite matrix Q_t . The DCC-GARCH model estimation is a two stage process. First we are estimating univariate GARCH model for each series. In the second stage, we analyze the conditional correlation using the standardized residual (estimated residual divided by conditional standard deviation) obtained from the first stage.

b) Wavelet Multi Resolution Analysis:

A brief review of the methodology proposed by Macho (2012) for evaluating wavelet multiple correlation and wavelet multiple cross- correlation is discussed below. Let $\{X_t\}$ be a multivariate stochastic process and let W_{jt} be the respective J^{th} level wavelet coefficients obtained by the application of MODWT. The wavelet multiple correlation (WMC henceforth) $\emptyset x$ (λ_j) can be defined as the can be defined as one single set of multi scale correlations calculated from X_t as follows.

At each wavelet scale λ_j we calculate the square root of the regression coefficient of determination in that linear combination of variables $W_{ijt}, i = 1,2, \dots n,$ for which such coefficient of determination is a maximum. In practice, none of these auxiliary regressions need to be run since, as it is well known, the coefficient of determination corresponding to the regression of a variable Z_i on a set of repressors $\{Z_k, k \neq i\}$, could be obtained as $R_i^2 = 1 - 1/\rho^{ii}$,where ρ^{ii} is the diagonal element of the inverse of the complete correlation matrix P. Therefore $\emptyset x$ (λ_j) could be obtained as

$$\emptyset x\,(\lambda j) = \phi_X(\lambda_j) = \sqrt{1 - \frac{1}{\max diag\, P_j^{-1}}} \quad \dots\dots\dots\dots\dots\dots\dots (6)$$

Where, P is the $N \times N$ correlation matrix of W_{jt}, and the $\max diag(.)$ operator selects the largest element in the diagonal of the argument.

Since the R_i^2 coefficient in the regression of a Z_i on the rest of variables in the system can be shown to be equal to the correlation between the observed values of Z_i and the fitted values of Z_i, obtained from such regression, we have that $\emptyset x$ (λj) can also be expressed as

$$\phi_X(\lambda_j) = Corr(\omega_{ijt}, \widehat{\omega_{ijt}}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \quad (7)$$

$$= \frac{Cov(\omega_{ijt}, \widehat{\omega_{ijt}})}{\sqrt{Var(\omega_{ijt})}\sqrt{Var(\widehat{\omega_{ijt}})}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \quad (8)$$

Where, W_{ijt} is chosen so as to maximize $\phi_X(\lambda_j)$ and $\widehat{w_{ijt}})$ are the fitted values in the regression of wij on the rest wavelet coefficients at scale λ_j

Allowing a lag t between observed and fitted values of the variables selected as the criterion variable at each scale λ_j, we may define the wavelet multiple cross-correlation (WMCC henceforth) as

$$\phi_{X,\tau}(\lambda_j) = Corr(\omega_{ijt}, \widehat{\omega_{ijt+\tau}}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

$$= \frac{Cov(\omega_{ijt}, \widehat{\omega_{ijt}})}{\sqrt{Var(\omega_{ijt})}\sqrt{Var(\widehat{\omega_{ijt+\tau}})}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (10)$$

For n=2 the WMC and WMCC are the same as the standard wavelet correlation and cross correlation.

4. EMPIRICAL RESUTS:

Table - 2. Pair- Wise Correlation Matrix Between Exchange rates

	India	Korea	Malaysia	Singapore	Japan	Indonesia	China
India	1						
Korea	0.3582	1					
Malaysia	0.3161	0.4844	1				
Singapore	0.3570	0.5406	0.6850	1			
Japan	0.0307	0.1519	0.2022	0.4388	1		
Indonesia	0.1878	0.4746	0.6006	0.5903	0.1412	1	
China	-0.0146	0.0239	0.0162	0.0651	0.1782	0.0058	1

Table 1 shows the descriptive statistics of the return data series. The average log returns of all countries are positive except in the case of Singapore dollar. On considering standard deviation as an indicator of exchange rate return volatility, it is clearly evident that it is comparatively high in Korea and low in China. The Jarque–Bera statistic rejects the null hypothesis of normality for all return series. Furthermore, all the returns series are leptokurtic, having significantly fatter tails and higher peaks. It can be seen from table 1 that kurtosis statistics are greater than three. KPSS test is used to check the stationarity of the data series. Exchange rate return series of all countries are found to be stationary at one percent level of significance. Table 2 shows the correlation matrix of exchange rate return series.

Table. 3 Multi- Variate GARCH, Dynamic Conditional Correlation

	India		Korea		Malaysia		Singapore	
Variables	Estimate	Std.Error	Estimate	Std.Error	Estimate	Std.Error	Estimate	Std.Error
μ	0.001118**	0.000493	-0.001016*	0.000552	-0.000041*	0.000021	-0.000708**	0.000346
ω	0.003100	0.000003	0.000019***	0.000007	0.074003	0.00005	0.000005***	0.000001
α	0.07303	0.067233	0.66638***	0.242372	0.267494***	0.066809	0.250752***	0.053881
β	0.907581***	0.067045	0.33262***	0.091215	0.724282***	0.069256	0.610648***	0.069249
	Japan		Indonesia		China			
Variables	Estimate	Std.Error	Estimate	Std.Error	Estimate	Std.Error		
μ	0.000041	0.000761	0.001177***	0.000397	0.000028	0.000363		
ω	0.000023	0.000002	0.000006***	0.750002	0.000003	0.00001		
α	0.0000034	0.000047	0.638233***	0.102746	0.062844	0.119687		
β	0.999***	0.000043	0.360767***	0.065606	0.899375***	0.267449		
dcca1	0.023993***	0.007023						
dccb1	0.932443***	0.932443						
Information Criteria								
Akaike		-55.856						
Bayes		-55.174						
Shibata		-55.913						
Hannan- Quinn		-55.582						

Source: Author's own calculation

Note: *** denotes significance at 1% level, ** significance at 5% level, * significance at 10% level

If we take 40 percentages and above as a bench mark for high correlation between the countries, pair- wise correlation between Korea –Singapore, Korea – Indonesia, Malaysia -Singapore, Malaysia -Indonesia, Singapore - Japan, and Singapore – Indonesia seems to be high. There are few other pairs, where the return correlation is marginal, i.e., less than 1 percentage. This includes Japan - India, India – China, Korea – China, Malaysia – China, Singapore –China, and Indonesia-China. The correlations of the rest of the pairs lie between 1 and 40 percentages. Though the correlation matrix gives a broad idea of inter-linkages of exchange rate return between the countries, we cannot deduce whether one country's Forex market reacts to shocks from other countries. Therefore, we fit a GARCH- DCC model and also calculate the Wavelet multiple correlation estimates to check the strength and depth of shock and volatility transmission.

Figure -1: Dynamic Conditional Correlations between Exchange rates

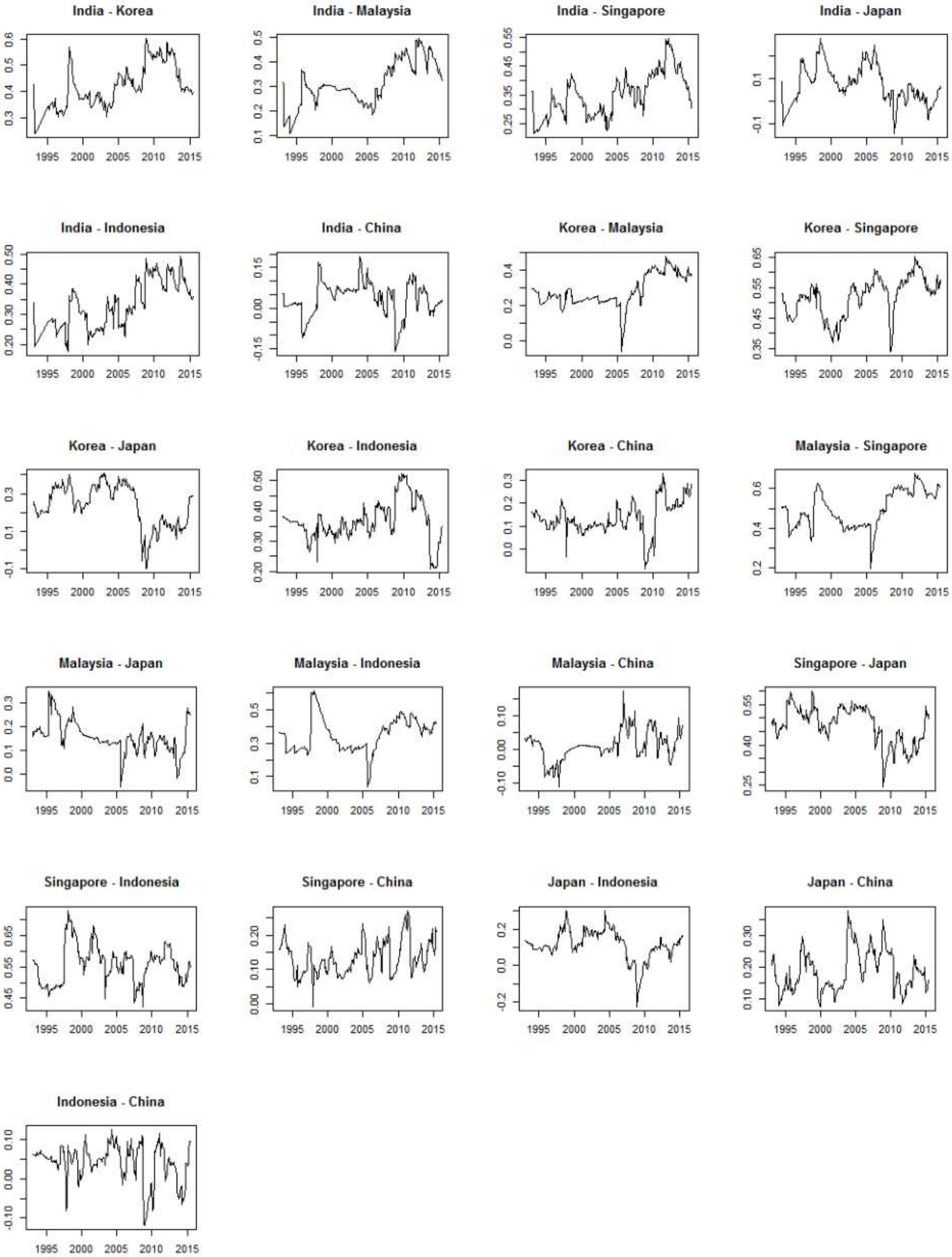
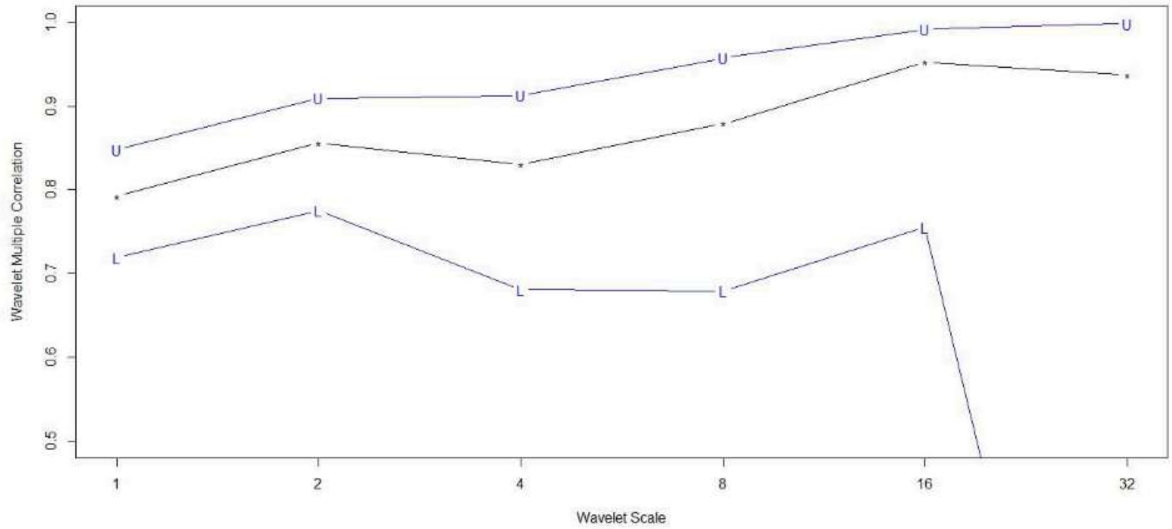


Table 4 shows result from Mulitivariate DCC model. The univariate coefficents are shown which are calculated using the two step procedure of the DCC model. In any of the cases, the sum of α and β does not exceed 1, which is a necessary criteria for the validity of univariate GARCH model. The estimated DCC coefficents a1 and b1 are positive and statistically significant at 1% level. These estimated coefficients sum up to a value which is less than one, implying that the dynamic conditional correlations of all exchange rate returns are mean reverting. The Dynamic Conditional Correlation graph (Figure 1) gives interesting results of shocks and persistence spillover during the study period. According to the intensity of correlation, we have classified the pairs of countries into three catagories; i) low correlation pairs; *i.e.* pairs of countries with correlation values that lie in the range of -0.01 to 0.02, ii) medium Correlation pairs with values of correlation between pairs that lie between 0.00 to 0.30, and iii) high correlation pairs where the values of correlation between pairs lie in the range of 0.00 to 0.50.

1. Low correlation pairs (Range between -0.02 to 0.02): India–Japan, India–China, Malaysia–China, Singapore–China, Japan–Indonesia, Indonesia-China.
2. Medium correlation pairs (Range between 0.00 to 0.30): Korea- Japan, Korea – China, Malaysia- Japan, Japan–China.
3. High correlation pairs (Range between 0.00 to 0.50 and above): India-Korea, India-Malaysia, India-Singapore, India–Indonesia, Malaysia-Korea, Korea-Singapore, Korea–Indonesia, Malaysia-Singapore, Malaysia–Indonesia, Singapore–Japan, Singapore–Indonesia.

The above classification shows that majority of pairs belong to the third group where the correlation is significantly high. It also should be noted that only two pairs, Malaysia-China and Indonesia-China, have correlation between -0.01 to 0.01. On the other hand, four pairs of countries namely India- Korea, India- Singapore, Korea- Singapore, Malaysia-Singapore, have the highest correlation. However, since the information about interdependencies between all these markets together is not captured by DCC method, we extend our analysis using Wavelet mulitple correlation methods. Multiple correlation analysis allows us to deduce information on interdependencies and overall integration of the above markets without limiting the study to pairwise analysis of correlations. It also helps us in analyzing the underlying correlation structure between markets at different time scales enabling one to extract information from varying time horizons of interest.

Figure 2: Wavelet Multiple Correlation



The wavelet multiple correlation with upper and lower bound of 95 percentage confidence intervals obtained from all of the seven forex markets is shown in figure 2. It can be seen that all markets are linearly related with correlations varying from 0.7 to 0.9 across all six time-scales. Evidence of strong positive correlations across all six scales, associated with periods of 1-2, 2to 4, 4 to 8, 8to16, 16 to 32, and 32 to 64 months, are observed with correlations increasing with the increase in time horizon. The correlations at the fifth and sixth wavelet scale which captures the long run time scale dynamics, associated with roughly 16 to 32 and 32 to 64 month oscillations, are very strong suggesting a perfect integration of the seven forex markets at the longest time scales.

Figure 3: Wavelet Multiple Cross- Correlation

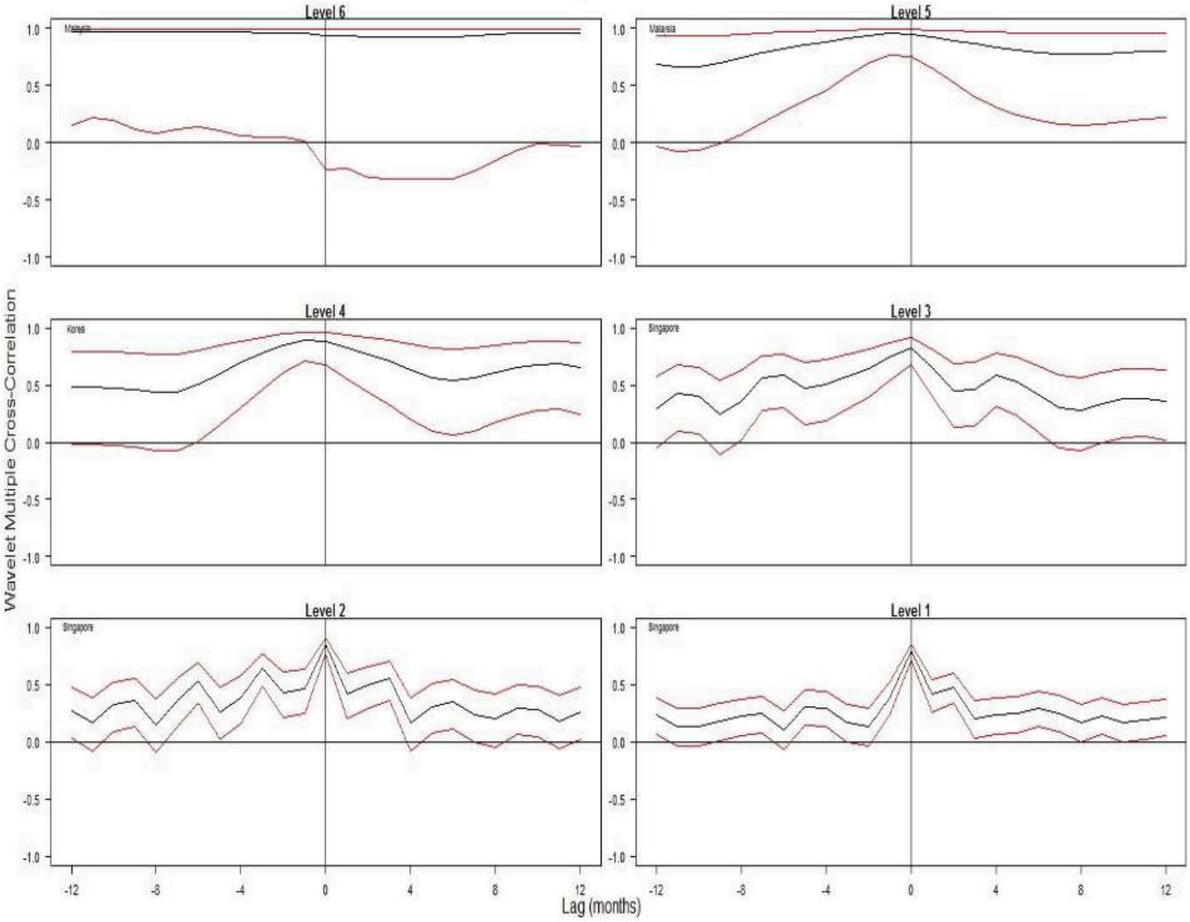


Figure 3 shows the wavelet multiple cross-correlations between the seven Forex markets obtained for six levels of time-scale decomposition with leads and lags up to twelve months. The variable that maximizes the multiple-correlation against a linear combination of rest of the variables is shown in the upper-left portion of each wavelet scale plot signaling a potential leader or follower for the whole system. We can see that the multiple cross-correlation increases with the time horizon just like the contemporaneous wavelet multiple correlation as observed before. Moreover, all cross-correlations appear significant for the majority of leads and lags for the first five levels of wavelet decomposition. The cross-correlation plot for the level 1 wavelet decomposition, which corresponds to a period of 1-2 months, reveals some leads (negative lags) that are not significant at the 5% level where the corresponding positive lags are clearly significant. This results in a slight asymmetry (right-skewness) in the plot which may indicate that the forex market of Singapore has a slight inclination to lead the other seven forex markets at the monthly scale. This phenomenon of right-skewness is also evident in the cross-correlation evaluated for the next four levels of decomposition where the forex market of Singapore leads other markets at the second and third level, with the exception of level four in which the Korean market (8 to 16 month scale) seems to lead other markets and level five where Malaysian market (16 to 32 month scale) lead other markets. Hence we can conclude that the forex market of Singapore is a potential leader in the short run time horizon of one month to eight months whereas the Korean market leads other markets at an annual scale. However, in the long run time horizon of 16 to 32 month time scale, Malaysian market is identified as the potential leader.

5. CONCLUDING REMARKS:

The focus of this paper was to check co-movements of forex market by examining pair- wise transmission of volatility between major Asian Forex markets and to check the overall integration of markets. The analysis using DCC-GARCH shows that there is significant volatility transmission between the selected countries during the study period. When we classified the pairs of countries based on the range of correlation, most of the pairs belonged to the third group indicating significantly high correlation ranges over the stuyd period. On the other hand, wavelet multiple correlation analysis of the seven forex markets revealed the existence of strong correlation between all the seven markets, with correlations increasing with the increase in time horizon, which can be interpreted as the existence of a nearly perfect integration of the seven markets at the longest time scale which captures 16 to 64 month time horizon. Moreover, wavelet multiple cross-correlation analysis identified markets of Singapore and Korea as potential leaders at short/medium time scales with Malaysian market leading other markets in the long run.

Our analysis of volatility transmission revealed the increase in integration of Asian forex market which is also supported by the increasing trend of integration across countries at global level. This integration could be the result of large level financial and capital flows and increased foreign trade relation between India and Asian countries especially in the last couple of decades. This analysis will be useful for government to formulate proper exchange rate policies considering the linkage with other Asian forex market and also for forex market investors to select their portfolio accordingly.

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