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Exchange Rate Return Co-movements and Volatility Spillover: The Case of Emerging Market Economies

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Abstract

The paper examines the return co-movements and volatility spillover among four major foreign exchange markets and four emerging markets. In particular the return co-movement and the volatility spillover between the foreign exchange markets of India, China, Brazil and South Africa and several other currencies namely the Euro, Japanese Yen, Australian Dollar and Swiss Franc for the period 1995-2015 is the main objective of the study. Based on daily data, the paper estimates a flexible MGARCH-Dynamic Conditional Correlation model and VAR-based spillover index. The econometric estimation suggests the presence of significant return co-movement and volatility spillover between the foreign exchange markets with emerging markets as the net receiver of volatility and developed markets as the net transmitter of volatility.

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Key Words: Exchange Rate, Emerging Market, Volatility, MGARCH-DCC Model, Return Co-movement, VAR based Spillover Index.

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1. INTRODUCTION

The appearance that immediately importunes in the mind with the word ‘volatile’ is that of unstable stock market, balance of payments crisis of the late 1990s or the unpredictable capital flows in the emerging market economies. But over the last decade the perception of volatility had widened and began to develop itself into an independent field of inquiry in the foreign exchange market as well. Conceptually volatility can be decomposed into a predictable component and an unpredictable component. In common dialect, it is a arduous task to make a distinction among volatility, uncertainty, risk, variability, fluctuation or oscillation but according to Knight’s (1921) volatility is allied to risk in that it provides a measure of the possible variation or movement in a particular economic variable or some function of that variable over some historical period. Mainly there are two key essence of volatility namely variability and uncertainty - variability in an economic variable may be anticipated while the residual which captures pure risk or uncertainty is unanticipated and constitutes a ‘shock’. The size and persistence of such shocks can pose a major challenge to the economic management as it can evolve into extreme volatility or a crisis. In addition volatility in exchange rate can be explained in the presence of three possible factors - volatility in market fundamentals, changes in expectations due to new information and speculative “bandwagons” (Engel and Hakkio 1993). Volatility in market fundamentals such as the money supply, income and interest rates affects volatility in exchange rate as exchange rate is a function of these fundamentals. Changes in expectations about future market fundamentals or economic policies also affect exchange rate volatility as new information induces the market participants to alter their forecasts of future economic conditions and policies thereby leading to exchange rate volatility. Finally volatility in exchange rate can be caused by speculative bandwagons or speculative exchange rate movement unrelated to current or expected market fundamentals.

In particular exchange rate is defined as the relative price of currencies between two or more countries, its behavior impacts the competitiveness of exports, international investment portfolios, international reserves and currency value of debt payments and more precisely impacts the overall stability of the economy. So any misalignment in the exchange rate thus requires intervention in the exchange market through appropriate exchange rate policy along with monetary and fiscal policies to ensure stability and growth in the economy. Nonetheless as the emerging markets progressed towards floating exchange regime and got more associated with the world financial market, the chances of volatility in exchange rate had increased manifold and managing such periods of volatility has emerged as a great challenge in view of the impossible trinity of independent monetary policy, open capital account and exchange rate management for nearly a decade. Therefore on this backdrop it calls for understanding the nature of volatility and anticipate and manage its consequences should be of considerable interest to policymakers as empirical investigation had increasingly shown that weak policies and institutions in developing countries magnifies the negative impact of volatility and can lead to permanent setback relative to richer countries.

This study investigates the exchange rate return co-movement and volatility spillover between four emerging foreign exchange markets of India, China, Brazil and South Africa and several other currencies namely the Euro, Japanese Yen, Australian Dollar and Swiss Franc. The notion of correlation reveals the nature of interdependencies among assets whereas the knowledge of spillover helps in understanding the proliferation of shocks from one market to another. Even though a variety of techniques could be applied to assess the return co-movement and volatility spillover but the most plausible among them is the Dynamic Conditional Correlation model and Vector Autoregression framework.

The structure of the paper is as follows: Section 2 provides with a review of the existing literature on the subject and section 3 delineates the econometric methodology and the data used in the study. Section 4 presents the empirical results. Section 5 concludes with summary of major findings and policy implications.

2. Review of Literature

A large number of literatures have primarily focused on the stock market volatility spillover with little emphasis on the foreign exchange markets. However, in the past decade there came the necessity to examine the return co-movement and volatility in foreign exchange market as it became more integrated with the world market. There is substantial literature on developed economies concerning the occurrence of volatility in exchange rates and its spillover effects to other foreign exchange markets with the papers emphasizing on the causes and methods of testifying volatility in exchange rate by employing GARCH family models. However, there is a dearth of literature in the context of co-movement and spillover in case of emerging economies as majority of the papers have largely concentrated on the role of intervention policy of the central bank in controlling volatility. A brief review of the existing papers is presented below.

While there are many approaches to measure volatility but the most common among them is the generalized autoregressive conditional heteroskedasticity model. The basic GARCH family models are frequently applied and quoted to describe the volatility in financial markets such as stock exchanges and foreign exchange markets. GARCH estimates of volatility are calculated using a time series of past exchange rate changes. Mundaca (1991) showed that GARCH models perform better than the ARCH model (Johnston and Scott 2000, Chong et al. 2002, Mckenzie & Mitchell 2002) whereas Sandoval (2006) captured the important characteristics of daily exchange rate by applying ARMA, GARCH, EGARCH and GJR-GARCH models (Kocenda and Valachy 2006). Giannellis and Papadopoulos (2011) use monetary, real and financial variables to assess the relevant importance of each of the variables to exchange rate volatility even as Erdemlioglu, Laurent and Neely (2012) modelled the volatility in exchange rate by incorporating intraday periodicity, autocorrelation and discontinuities in prices. Djeutem and Kasa (2013) shows that revision of robust forecasts are more volatile than revisions of non-robust forecasts in the context of the monetary model of exchange rates. In another paper, Stancik (2007) states that more openness leads to lower volatility, effect of news varies across countries and only key changes in exchange rate regimes have significant effect on exchange rate volatility while Annachhatre (2013) argues that exchange rate volatility is caused due to deviation from fundamentals, excessive speculative activities, macro-economic shocks or other global and domestic news. On the other hand Alam and Rahaman (2012) explored that both AR and ARMA models best suits the in-sample data and GARCH and TARCH model suits the out-of-sample data. Similarly Kamal, Haq, Ghani & Khan (2012) also exhibited that EGARCH model best explains the volatile behavior of the daily exchange rate (Narayan et al. 2009). These deliberations indicate that the variance of daily exchange rate changes is forecastable using GARCH models.

Regarding volatility spillover, studies that examined exchange rate volatility transmission were initiated by Engle et al. (1990) where the authors found supporting evidence for two hypotheses namely the ‘heat waves’ and the ‘meteor shower’. Heat waves refer to exchange rate volatility in one particular market having only country specific effect while the meteor shower refer to volatility being transmitted to other countries.[3] Ross (1989) note that volatility is an important source of information in the financial markets and the first channel of volatility spillover is news which affects a set of financial variables simultaneously (Bollerslev et al. 1992) whilst the second channel operates through the information spillover caused by the cross market hedging (Ederington & Lee 1993). Moreover the contagion hypothesis notes that agents who observe a price decline in one market becomes more risk averse and reduces their position in the other markets thereby creating an apparent spillover effect (Ebrahim 2000). Anderson et al. (1999) reported a normality-inducing volatility transmission, high contemporaneous correlation across volatilities, high correlation between correlation and volatility, pronounced and highly persistent temporal variation in both volatilities and correlation and clear evidence of long memory dynamics in both volatilities and correlation. Inagaki (2007) uses residual cross-correlation function to investigate the volatility spillover from the euro to the pound. Antonakakis (2012), in a DCC and VAR framework, suggested that euro is the net transmitter of volatility while pound is the net receiver of volatility. Moreover the cross-market volatility spillovers are bidirectional and the highest spillovers occur between European markets (Chowdhury and Sarno 2004). Perez-Rodriguez (2006) employs the DCC model to find evidence of significant volatility spillovers between the euro, yen and the pound and that correlations are high between the euro and the pound. Under a similar approach Kitamura (2010) finds significant volatility spillovers between the euro, pound and the franc and that the pound and franc are highly integrated to the euro market. Nikkinen et al. (2006), in a VAR framework, found that correlation is highest between Euro and Franc. Likewise Diebold and Yilmaz (2009), in a VAR framework, found remarkable facts of contradictory performance in the dynamics of return spillovers and volatility spillovers in the context of nineteen global equity markets.[4] Kearney and Patton (2000) pointed out both direct and indirect volatility transmission within the EMS and the results further hold up the conjecture that markets are more likely to transmit volatility in active phases rather than in calm ones (Ghose and Kroner 1996, Andersen and Bollerslev 1998). The study by Sahoo (2012) marked the volatility transmission from Brazilian

[3] Accordingly, enquiry in this field were carried out by Bollerslev (1990), Speight and McMillan (2001), Melvin and Melvin (2003), Black and McMillan (2004) and Calvet et al. (2006). The main feature of these studies is the application of GARCH family models to assess volatility dependencies across currencies.

[4] See also Diebold and Yilmaz (2012)

real, the Russian ruble, the South Korean won, the Singapore dollar, the Japanese yen, the Swiss franc, the British pound sterling and the euro to the exchange rate of the Indian rupee and Hong (2001) proved the existence of granger causality between two weekly nominal US Dollar exchange rates with respect to Deutsche Mark and Japanese For instance, Ghosh (2012) displayed that volatility has actually spilled over from stock market, government securities market, forward market, derivative market and international crude prices to the Indian foreign exchange market. In addition the stock market volatility emerged as the most important factor influencing volatility spillover in the foreign exchange market (Mishra et al. 2007). Mukherjee (2011) had theorized that return volatility of the Indian equity market exhibits a sudden sharp increase and the conditional correlation of the equity return with all other markets has increased over time much as Lee (2010) who suggested the presence of both regional spillover and the transmission of shocks from external stock and foreign exchange markets. Yet Saha and Chakrabarti (2011) displayed volatility spillover with no asymmetric impact between stock to exchange rate market and vice versa. Cappiello et al. (2006) demonstrated that equity returns show strong evidence of asymmetries in conditional volatility. Behera (2011) signifies that Non-Deliverable-Forward market (NDF) shocks and volatilities influence the onshore markets. Horng and Chen (2010) unfolded that exchange rate volatility negatively affects Thailand's stock market and Japanese stock return volatility affects the variation risks in the Thailand's stock market. Song (2009), using MGARCH models, witnessed significant volatility spillover between Shanghai and Shenzhen stock markets. To finish with Fang et al. (2006) suggest that within the domestic cross markets, the volatility transmission is unidirectional from the stock market to the bond market. But in case of international cross-market analysis, there is a strong evidence of volatility spillover among the international stock markets than between international stock and bond markets.

A wide range of unending literature is furnished above which gives an idea about the occurrence of volatility in the foreign exchange markets. Nevertheless the preceding section also provides a view of the co-movement and volatility spillover among different currencies and the process of modelling that spillover and analyzing the consequences. Consequently the next section will present a detailed econometric analysis of the return co-movement and volatility spillover and interpret the results.

3. THE DATA AND METHODOLOGY

3.1. The Data

The study focuses on the period 1995-2015 using daily exchange rate of Euro, Japanese Yen, Australian Dollar, Swiss Franc, Indian Rupee, Chinese Yuan, South African Rand and Brazilian Real respectively. These series were extracted from Federal Reserve Bank database. The rationale behind choosing Euro, Japanese Yen, Australian Dollar and Swiss Franc is that according to the Bank for International Settlements (BIS) (2013), these currencies are rated as the most traded currency among others. The BIS's Triennial Central Bank Survey on the turnover of these currencies in 2013 are \$ 1,785,720 million, \$ 1,231,249 million, \$ 4,61,689 million and \$ 2,75,472 million of all transactions including the spot transactions, outright forwards, foreign exchange swaps, currency swaps and foreign exchange options. It is also worth mentioning here that according to the European Central Bank, the conversion of European Currency Unit (ECU) to Euro on 1st January, 1999 was at 1:1 basis.

Before proceeding with the estimation, the variables were tested for non-stationary behaviour. The stationarity test based on Augmented Dickey-Fuller (Table 1) rejects the null hypothesis of unit roots in exchange rate at the first difference. Further a detailed view of the descriptive statistics and the time path of the variables (Figure 1) will help in signifying that most of them show abnormal movement during the period of analysis. The return of each foreign exchange is calculated by taking the first logarithmic differences in exchange rate denoted as:

$$\Delta \ln S_t = \ln S_t - \ln S_{t-1}$$

A close view at the return series (Figure 2) of the variables reveals the presence of volatility clustering and ARCH effect which is supportive of modelling the volatility in exchange rate in a GARCH framework.

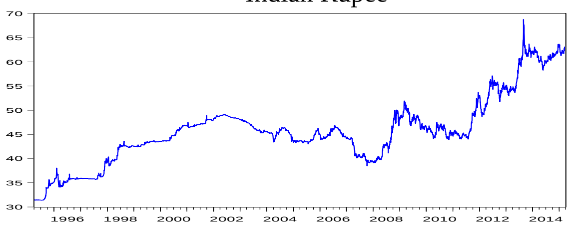
Table 1: Unit Root Test

Exchange Rates	ADF at Level	ADF at 1st difference
Indian Rupee	-1.638818	-29.80382*
Chinese Yuan	-1.402004	-28.61324*
Brazilian Real	-1.332779	-68.86502*
South African Rand	-1.819792	-71.37670*
Euro	-1.641437	-70.17663*
Japanese Yen	-2.250685	-70.65205*
Australian Dollar	-1.854496	-72.25537*
Swiss Franc	-2.800984	-70.70936*

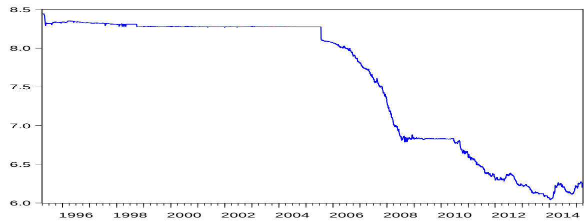
∗ denotes significance at 1% level

Figure 1: Time Path of the Variables
Emerging Market Economics

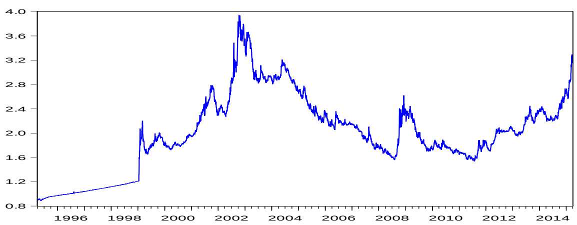
Indian Rupee



Chinese Yuan



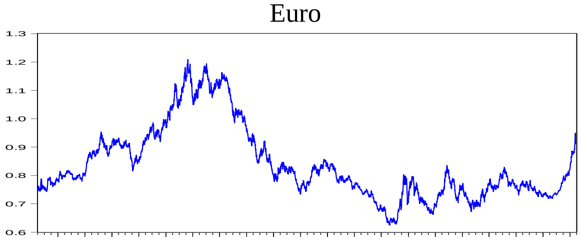
Brazilian Real



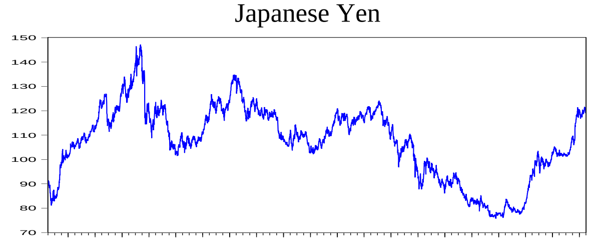
South African Rand

Developed Economies

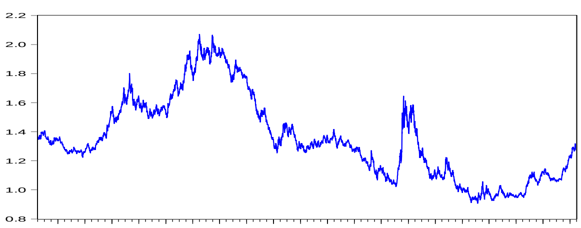
Euro



Japanese Yen



Australian Dollar



Swiss Franc

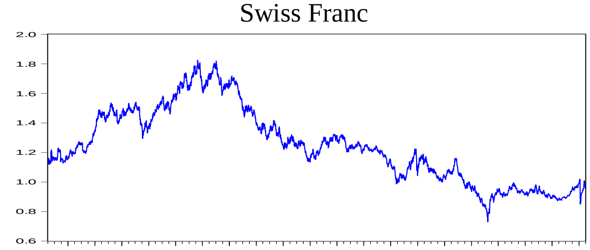
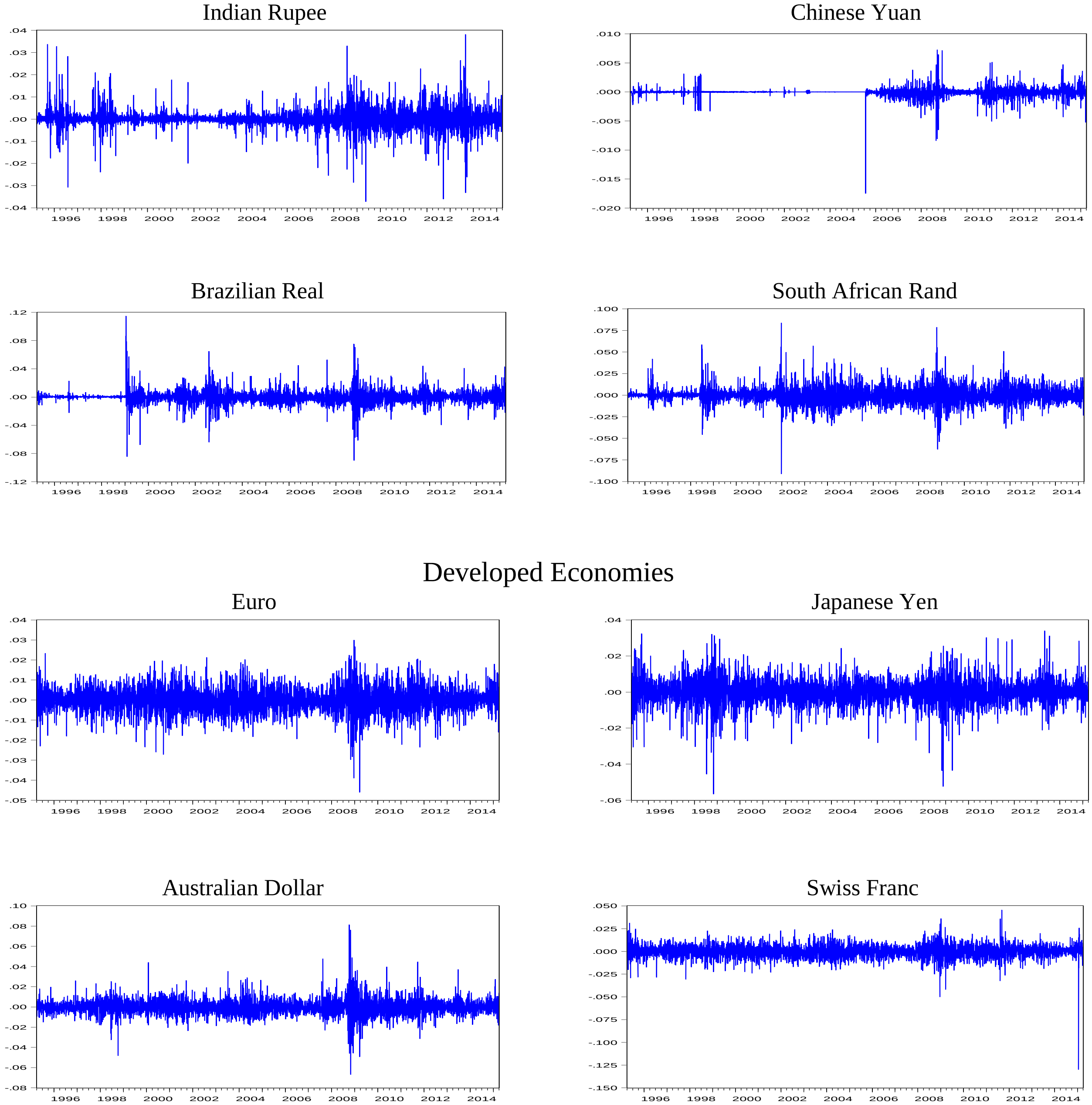


Figure 2: Return Series
Emerging Market Economies



3.2 The Methodology:

Time-varying volatility models have been popular since the early 1990s in empirical research in finance. The analysis of volatility in financial market has been widely studied in ARCH-GARCH framework pioneered by Engle (1982) and further developed by Bollerslev (1986), Nelson (1991) and others. To investigate the return co-movement among the foreign exchange markets, MGARCH-DCC model was put in place as this method explicitly takes into account the time-varying nature and interrelations among the markets. The Dynamic Conditional Correlation (DCC) model was proposed by Engle (2002)[5] as an attempt to establish that correlations, both conditional and unconditional, among the markets are not constant rather time-varying. The model works in two steps. In the first step, the individual conditional variances are specified as univariate GARCH processes and in the second step the correlation among the series is presented. The model has a computational advantage over other MGARCH models in that the number of parameters to be estimated in the process is independent of the number of series to be correlated. As a result, very large correlation matrices can be estimated. Nonetheless it is an investigation against the too restrictive assumption of constant correlation of Constant Conditional Correlation (CCC) Model. The DCC model is represented as

$$y_t = \mu_t(\theta) + \epsilon_t, \quad \text{where } \epsilon_t|\Omega_{t-1} \sim N(0, H_t) \qquad \text{….(1)}$$

$$\epsilon_t = H_t^{1/2} u_t, \quad \text{where } u_t \sim N(0, I)$$

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

where $y_t = (y_{it} \ldots \ldots y_{nt})'$ is a $n * 1$ vector of exchange rate return, $\mu_t(\theta) = (\mu_{it}, \ldots \ldots, \mu_{nt})'$ is the conditional $n * 1$ mean vector of y_t, H_t is the conditional covariance matrix, $D_t = diag(h_{iit}^{1/2} \ldots \ldots h_{nnt}^{1/2})'$ is a diagonal matrix of square root conditional variances, where h_{iit} can be defined as any univariate GARCH type models and R_t is the $t * (n(n-1)/2)$ matrix containing the time varying conditional correlations defined as

$$R_t = diag\left(q_{ii,t}^{-1/2} \ldots q_{nn,t}^{-1/2}\right) Q_t \, diag(q_{ii,t}^{-1/2} \ldots q_{nn,t}^{-1/2}) \text{ or } \rho_{ij,t} = \rho_{ji,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{jj,t}}} \qquad \text{….(3)}$$

where $Q_t = (q_{ij,t})$ is a $n * n$ symmetric positive definite matrix given by

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1} \qquad \text{….(4)}$$

where $u_t = (u_{1t}, u_{2t}, \ldots . u_{nt})'$ is the $n * 1$ vector of standardized residuals, $\overline{Q}$ is the $n * n$ unconditional variance of u_t and α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$.

All the flexible versions of the MGARCH models are estimated under a multivariate Student t distribution as the normality assumption is rejected in most empirical applications

[5] See also Bauwens et al. (2006).

dealing with daily exchange rate data[6]. This view is also endorsed by Bollerslev (1986), Heish (1989) and Baillie and Bollerslev (1989) who find evidence that GARCH (1,1) model with Students *t* distribution, rather than normal distribution, is the most appropriate for analyzing exchange rate data.

In order to study the volatility spillover among the foreign exchange market returns, the generalised vector autoregression structure (Koop et al. 1996 and Pesaran and Shin 1998) was used as this method produces variance decomposition which is invariant to the ordering of the variables. The generalised VAR approach allows correlated shocks and accounts for them accurately using the historically observed distribution of the errors. Since the shocks to each variable are not orthogonalised, the sum of the contributions to the variance of the forecast error is not necessarily one.

Consider a p-order N-variable VAR:

$x_t = \sum_{i=1}^{p} \varphi_i x_{t-1} + \epsilon_t$, where $x_t = (x_{it}, \ldots \ldots, x_{nt})$ is a vector of endogenous variables, $\epsilon_t \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-1}$, where NxN coefficient matrices A_i obey the recursion $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \ldots . + \varphi_p A_{i-p}$, with A_0 being an NxN identity matrix and with $A_i = 0$ for $i < 0$.

Denoting the KPPS H-step ahead forecast error variance decomposition as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i^{'} A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i^{'} A_h \Sigma A_h^{'} e_i)} \quad \ldots .(5)$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the jth equation and e_i is the selection vector with one as the ith element and zeros otherwise. As was mentioned above, the sum of the each row of the variance decomposition matrix is not equal to one, so each variable of the matrix is normalized by row sum, so that resultant row sum of the variables is equal to one. This is as follows

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \quad \ldots .(6)$$

with $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$ by construction.

[6] Harvey et al. (1992) and Fiorentini et al. (2003).

Using these results, the total volatility spillover index is constructed as

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} * 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} * 100 \qquad \text{....(7)}$$

This index measures the contribution of spillovers of volatility shocks across five markets to the total forecast error variance. Additionally, the directional spillovers received by market i from all other markets j are defined as

$$S_{i<}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} * 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} * 100 \qquad \text{....(8)}$$

Equally the directional spillovers transmitted by market i to all other markets j are defined as

$$S_{i>}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} * 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} * 100 \qquad \text{....(9)}$$

and finally the net volatility spillover from market i to all other markets j is defined as

$$S_{i}^{g}(H) = S_{i>}^{g}(H) - S_{i<}^{g}(H) \qquad \text{....(10)}$$

The net volatility spillover shows how much each market contributes to the volatility of other markets on average. In this context it is important to examine the net pairwise volatility spillover which tells us that the volatility spillover between markets i and j is simply the difference between the gross volatility shocks transmitted from market i to market j and those transmitted from market j to market i. It is represented by the following formula

$$S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)} \right) * 100$$

$$= \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} \right) * 100 \qquad \text{....(11)}$$

4. EMPIRICAL RESULTS

4.1 Descriptive Statistics

Table 2 reports the descriptive statistics of Indian Rupee, Chinese Yuan, Brazilian Real, South African Rand, Euro, Japanese Yen, Australian Dollar and Swiss Franc for the period 1995-2015.

Table 2: Descriptive Statistics

	Indian Rupee	Chinese Yuan	Brazilian Real	South African Rand	Euro	Japanese Yen	Australian Dollar	Swiss Franc
Mean	0.000132	-5.91E-05	0.000247	0.000234	3.90E-05	5.35E-05	-2.99E-05	-7.03E-06
Median	-3.60E-05	-7.61E-06	0.000158	0.000119	8.44E-05	0.000152	0.000137	-0.000180
Std. Dev.	0.004318	0.000730	0.009550	0.009724	0.005906	0.006791	0.006869	0.007635
Skewness	0.100569	-3.074689	0.488242	0.329507	-0.170353	-0.472464	-1.417929	0.702707
Kurtosis	14.64613	84.09503	20.12225	9.982374	5.423840	8.047721	30.25439	15.09329
Jarque Bera (Prob.)	29486.23 (0.000)*	1437490 (0.000)*.	63923.16 (0.000)*	10690.16 (0.000)*	1302.062 (0.000)*	5731.596 (0.000)*	163183.3 (0.000)*	32213.79 (0.000)*
Q(30)	80.245 (0.000)*	186.81 (0.000)*	99.482 (0.000)*	49.680 (0.013)**	19.305 (0.933)	46.693 (0.027)**	59.626 (0.001)*	30.799 (0.425)
$Q^2(30)$	1583.8 (0.000)*	138.80 (0.000)*	5416.9 (0.000)*	3111.9 (0.000)*	1415.0 (0.000)*	1042.1 (0.000)*	5311.5 (0.000)*	140.81 (0.000)*
Obs.	5216	5216	5216	5216	5216	5216	5216	5216

*Notes: *, ** indicates significance at 1% and 5% level. P-values are in the parentheses.*
Q(1) and $Q^2(1)$ is the Ljung-Box statistic for serial correlation in return series and squared series respectively

From the table, it is evident that the standard deviation values show that the returns of the foreign exchange markets are positive and highest for South Africa followed by Brazil, India and China. This result signifies that variation in South African Rand is more as compared to others emerging economies. The kurtosis coefficients points to the leptokurtic nature of the foreign exchange markets and the Jarque-Bera statistics indicate the presence non-normal distribution since all the coefficients are significant at one percent level thus rejecting the null hypothesis of normally distributed returns. Accordingly the table also reports the Ljung-Box Q and the Q^2 statistics for all the return series and the squared return series. The Q statistic results points to the fact that only Euro and Swiss Franc can be characterized as random walk processes. Alternatively the Q^2 statistic is significant for each return series indicating the presence of higher order serial correlation and non-linearity among the variables. These findings also strengthen the fact that exchange rate volatility can be modelled in a GARCH framework.

Furthermore the returns series of all the currencies exhibit non-randomness and volatility clustering which means that large movements are characterized by large changes and vice-versa.

This conclusion also finds evidence from the literature that exchange rate volatility can be modelled in a GARCH process.

4.2 Return Co-movement

In this section we look into the return co-movement of the emerging foreign exchange markets with world's four most traded currencies by applying Dynamic Conditional Correlation model. But before continuing with the estimation, the correlation among the variables is presented in table 3.

Table 3: Cross Correlation

	Euro	Japanese Yen	Australian Dollar	Swiss Franc
Indian Rupee	0.187661 (0.000)*	0.003984 (0.7736)	0.265589 (0.000)*	0.114220 (0.000)*
Chinese Yuan	0.067685 (0.000)*	0.006305 (0.6489)	0.089584 (0.000)*	0.042771 (0.0020)*
Brazilian Real	0.200760 (0.000)*	-0.016091 (0.2453)	0.365206 (0.000)*	0.086949 (0.000)*
South African Rand	0.387282 (0.000)*	0.007100 (0.6082)	0.507310 (0.000)*	0.262830 (0.000)*

*Note: * indicates significance at 1% level. P-values are in the parentheses*

These correlation coefficients determine the degree to which two variable's movements are associated. The table discloses that Indian Rupee, Chinese Yuan and South African Rand are positively correlated with Euro, Japanese Yen, Australian Dollar and Swiss Franc. On the other hand the Brazilian Real is also positively correlated with Euro, Australian Dollar and Swiss Franc but negatively correlated with Japanese Yen. It is important to note here that almost all the emerging markets have the highest significant positive correlation with Australian Dollar, Euro and Swiss Franc and nearly insignificant correlation with Japanese Yen. The positive correlation symbolizes that an appreciation of one currency leads to an appreciation of other and vice-versa and the negative correlation exhibits that an appreciation of one currency leads to depreciation of other and vice-versa.

We shall now focus on simple MGARCH-DCC(1,1) model for illustrating the return co-movement in the foreign exchange market. Four DCC model was estimated separately to understand the co-movements between the emerging markets with the developed foreign exchange markets. For instance, DCC model was conducted for Indian Rupee, Chinese Yuan, Brazilian Real and South African with the developed country's currency independently.

Table 4: DCC Estimate

Parameters	India Rupee	China Yuan	Brazilian Real	South African Rand
$\boldsymbol{\alpha}$	0.023353*	0.022847*	0.024284*	0.024712*
$\boldsymbol{\beta}$	0.974251*	0.974935*	0.973667*	0.973085*
$\boldsymbol{\alpha+\beta}$	0.997604	0.997782	0.997951	0.997797
Stability Condition $\boldsymbol{\alpha+\beta} < 1$	Met	Met	Met	Met

** denotes significance at 1% level*

Table 4 depicts the estimates of DCC parameters α and β to be statistically significant indicating that the second moments of exchange rate returns are time varying. Moreover the summation of the parameters are less than one in all the cases which signifies that the DCC model is very well specified as the stability condition is met.

Henceforth the univariate GARCH estimate of emerging market economies and the developed economies are presented in table 5 and table 6 respectively. The estimated outcomes through some light on how the nature and behaviour of the emerging foreign exchange markets vary from their developed counterparts.

Table 5: Univariate GARCH Estimate and Diagnostic Test: Emerging Market Economies

Countries	ARCH ($\boldsymbol{\gamma}$)	GARCH ($\boldsymbol{\delta}$)	$\sum(\boldsymbol{\gamma}+\boldsymbol{\delta})$	Status of the series	ARCH-LM test
Indian Rupee	0.254493*	0.808864*	1.063357	Explosive	0.003253 (0.8143)
Chinese Yuan	0.431677*	0.738855*	1.170532	Explosive	-0.000198 (0.9886)
Brazilian Real	0.164723*	0.869247*	1.03397	Explosive	-0.000356 (0.9795)
South African Rand	0.104427*	0.909714*	1.014141	Explosive	0.037116 (0.0073)*

*Note: * denotes significance at 1% level*

Table 6: Univariate GARCH Estimate and Diagnostic Test: Developed Economies

Countries	ARCH ($\boldsymbol{\gamma}$)	GARCH ($\boldsymbol{\delta}$)	$\sum(\boldsymbol{\gamma}+\boldsymbol{\delta})$	Status of the series	ARCH-LM test
Euro	0.031710*	0.967370*	0.99908	Persist for long time	-0.030392 (0.0282)**
Japanese Yen	0.037300*	0.954671*	0.991971	Persist for long time	0.024158 (0.0811)
Australian Dollar	0.041354*	0.953699*	0.995053	Persist for long time	-0.002195 (0.8741)
Swiss Franc	0.029869*	0.964356*	0.994225	Persist for long time	0.004962 (0.7202)

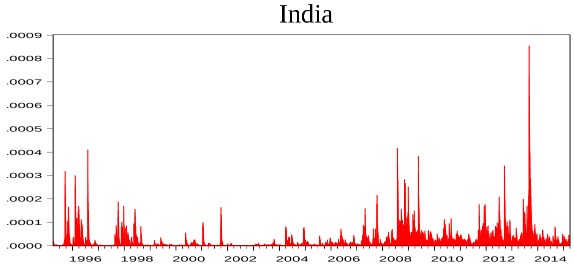
*Note: * and ** denotes significance at 1% level and 5% level*

In the case of emerging market economies, the summation of ARCH and GARCH coefficients are all greater than one which relates that the return series of the emerging foreign exchange markets are explosive thus pointing to the tendency to move away from the mean value (Kuruvila et al. 2012, Sekhar 2003) whereas the summation of ARCH and GARCH coefficients of the developed economies (Table 6) are less than one which means the volatility of the return series of the developed economies have a leaning to persist for a long time. Furthermore the conditional variances graphs (Figure 3) of the respective markets also strengthen the above argument. Nevertheless the ARCH-LM test confirms that no further ARCH effect exists in the returns series except in South African Rand and Euro.

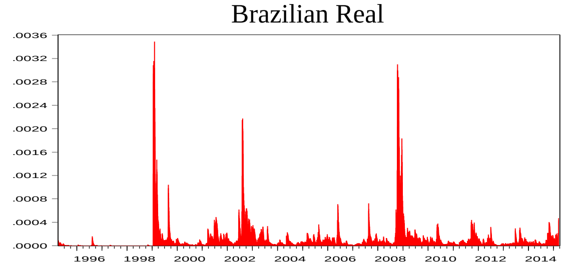
Figure 3: Conditional variance

Emerging Market Economies

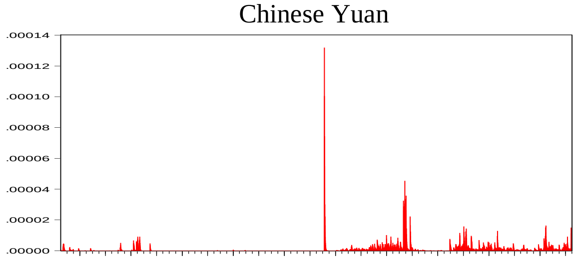
India



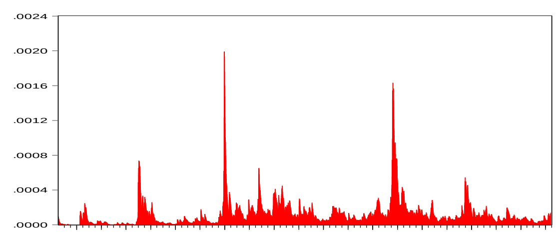
Brazilian Real



Chinese Yuan

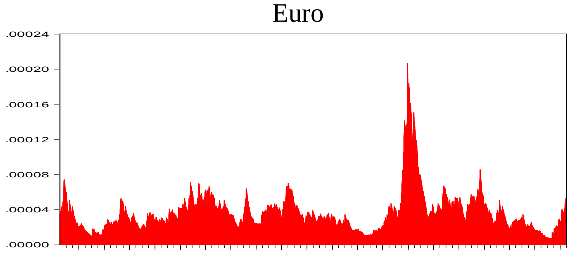


South African Rand

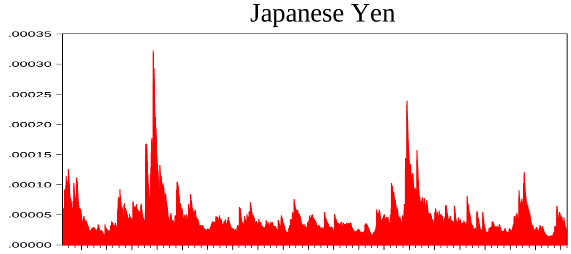


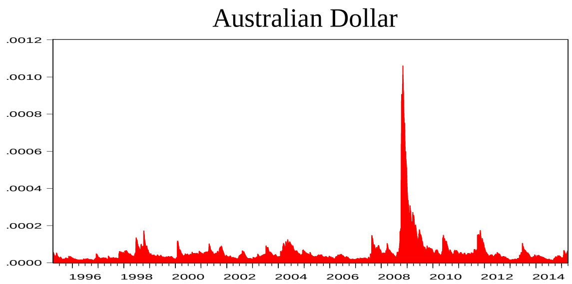
Developed Economies

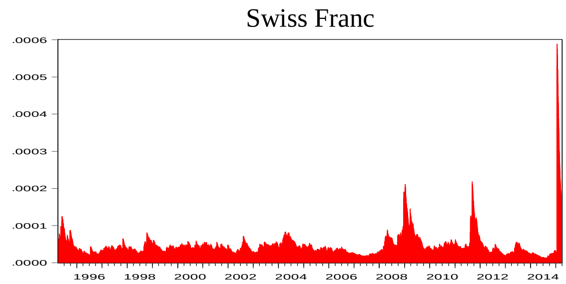
Euro



Japanese Yen





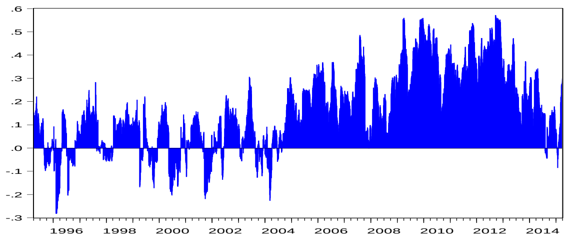


Besides the conditional correlation graphs (Figure 4) report evidence of significant dynamic conditional correlation among the emerging markets and developed markets. It is indicative that there is high positive correlation between Indian Rupee, Brazilian Real and South African Rand with Australian Dollar, Euro and Swiss Franc, but the degree of correlation, though positive, is small in case of Chinese Yuan. Conversely the correlation with Japanese Yen does not turn out any alluring conclusion. It is notable from the graphs that the correlation is relatively positive with the magnitude increasing particularly after the period 2004 to the end. It is also interesting to mark that the conditional variance curves reflect similar pattern during the same period. This increase in conditional variances and correlations are probably connected with extreme episodes of disorder or crises such as the Asian crisis of 1997-98, the Brazilian crisis of 1999, the recession in US and EU in early 2000s, the terror attack of 2001, the dollar crisis in 2005, the capital outflow from emerging markets following the signal from FED to increase the Fed Funds rate in 2006, the global financial crisis starting in 2007 and finally occurring in 2008 or the Eurozone debt crisis in 2011. The correlation figures further signifies that Indian Rupee, Chinese Yuan, Brazilian Real and South African Rand have a considerable co-movement with Euro, Australian Dollar and Swiss Franc. On the contrary it can as well be argued that the implied volatility of Euro, Australian Dollar and Swiss Franc significantly affects the volatility expectations of Rupee, Yuan, Real and Rand.

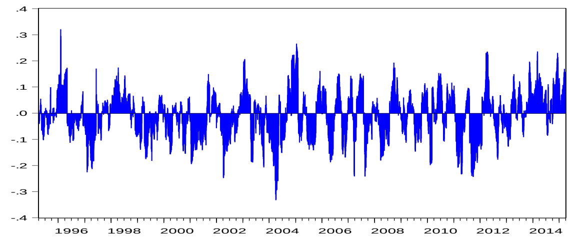
Figure 4: Dynamic Conditional Correlation

Indian rupee

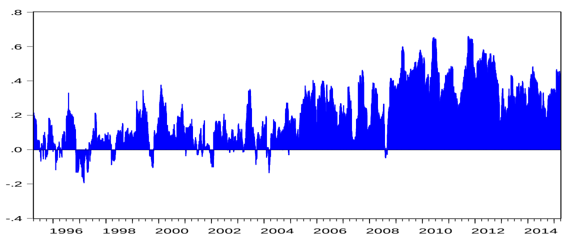
INR/Euro



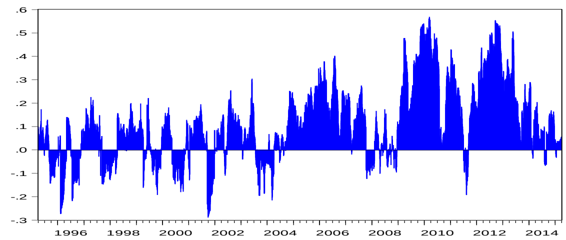
INR/Yen



INR/Australian Dollar

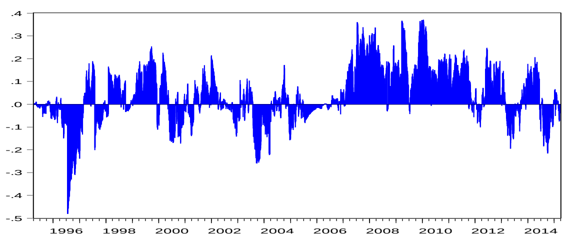


INR/Swiss Franc

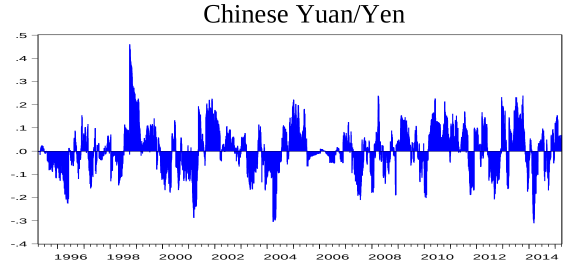


Chinese Yuan

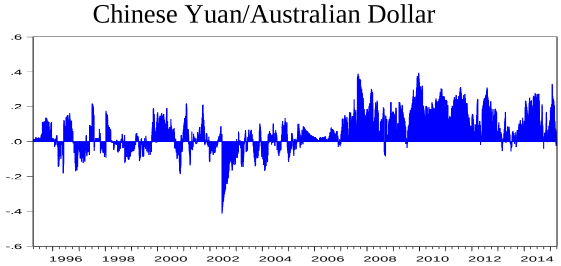
Chinese Yuan/Euro



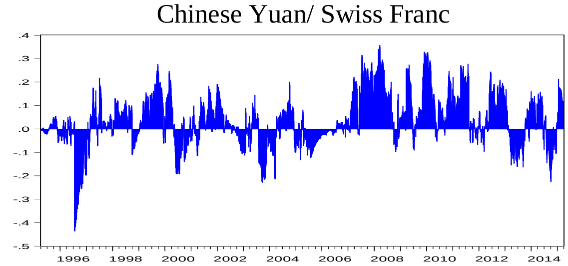
Chinese Yuan/Yen



Chinese Yuan/Australian Dollar

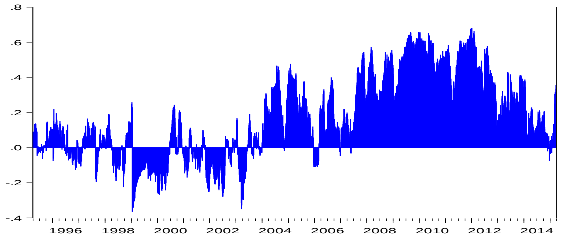


Chinese Yuan/ Swiss Franc

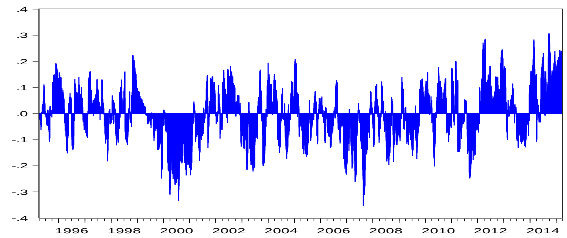


Brazilian Real

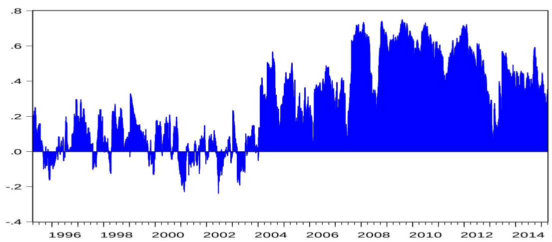
Brazilian Real/Euro



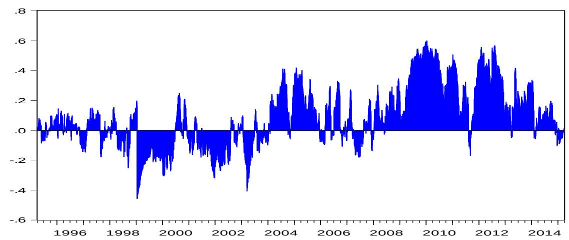
Brazilian Real/Yen



Brazilian Real/ Australian Dollar

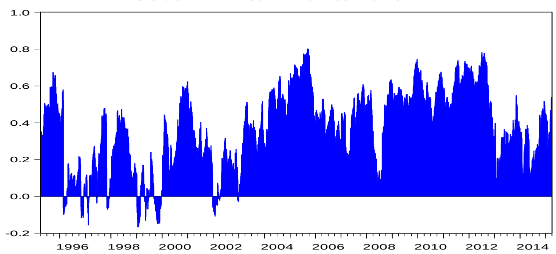


Brazilian Real/ Swiss Franc

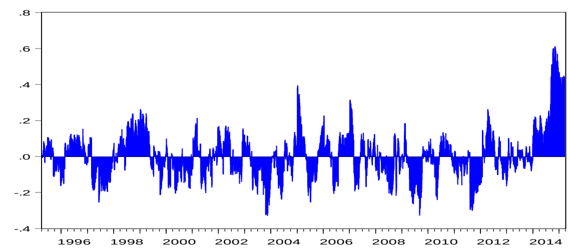


South African Rand

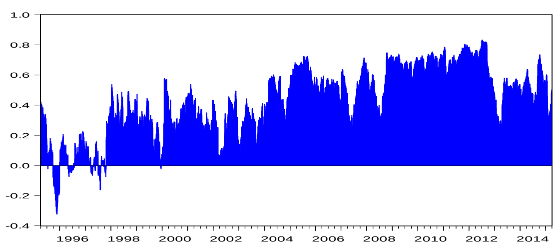
South African Rand/Euro



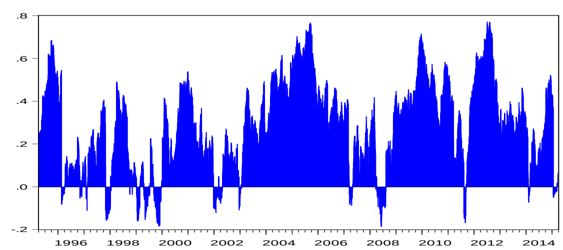
South African Rand/Yen



South African Rand/ Australian Dollar



South African Rand/Swiss Franc



4.3 Volatility Spillover

In this section, the estimate of the volatility spillover based on generalised vector autoregression process is presented. Specifically the variance decomposition technique is used to measure the volatility spillover between the foreign exchange markets. The results of the degree and direction of volatility spillovers within and across the four emerging market economies from developed economies are shown in table 7, table 8, table 9 and table 10 successively.

Before citing the results, it is essential to explain the rows and columns of the spillover table. The $ijth$ entry is the estimated contribution to the forecast error variance of market i coming from innovations to market j. The diagonal elements measure the own-market volatility spillover and the off-diagonal elements measure the cross-market volatility spillover. Therefore the off-diagonal column sum (Contributions to others) and row sum (Contribution from others) are the 'to' and 'from' volatility spillovers in each market and the difference between 'from and to' gives the net volatility spillover from market i to market j. The total volatility spillover index appears in the lower right corner of the table shows the grand off-diagonal column sum (row sum) relative to the grand column sum including diagonals (row sum including diagonals) expressed in percentage.

Table 7: Indian Rupee

	From					
To	Indian Rupee	Euro	Japanese Yen	Australian Dollar	Swiss Franc	Contribution From Others
Indian Rupee	88.849	3.347	0.003	6.484	1.317	11.151
Euro	1.836	51.811	0.001	12.630	33.722	48.189
Japanese Yen	0.005	0.002	99.833	0.148	0.012	0.167
Australian Dollar	5.119	16.985	0.051	69.568	8.277	30.432
Swiss Franc	0.739	36.477	0.012	6.686	56.086	43.914
Contribution to Others	7.700	56.812	0.066	25.948	43.327	133.854
Contribution including own	96.549	108.622	99.899	95.516	99.413	
Net Spillover	-3.451	8.623	-0.101	-4.484	-0.587	Spillover Index 26.771%

Notes: Values reported are the variance decomposition based on 10-step ahead forecasts. The VAR lag length of order 1 was selected by the Hannan-Quinn Criterion.

Table 8: Chinese Yuan

	From					
To	Chinese Yuan	Euro	Japanese Yen	Australian Dollar	Swiss Franc	Contribution From Others
Chinese Yuan	96.049	1.785	0.009	1.323	0.833	3.951
Euro	0.227	52.667	0.001	12.826	34.279	47.333
Japanese Yen	0.003	0.002	99.832	0.152	0.011	0.168
Australian Dollar	0.571	17.785	0.056	72.917	8.672	27.083
Swiss Franc	0.120	36.705	0.012	6.726	56.437	43.563
Contribution to Others	0.920	56.277	0.078	21.027	43.796	122.098
Contribution including own	96.970	108.944	99.909	93.944	100.233	
Net Spillover	-3.031	8.944	-0.09	-6.056	0.233	Spillover Index 24.420%

Notes: Values reported are the variance decomposition based on 10-step ahead forecasts. The VAR lag length of order 1 was selected by the Hannan-Quinn Criterion.

Table 9: Brazilian Real

	From					
To	Brazilian Real	Euro	Japanese Yen	Australian Dollar	Swiss Franc	Contribution From Others
Brazilian Real	84.535	3.453	0.042	11.288	0.682	15.465
Euro	2.083	51.674	0.001	12.590	33.652	48.326
Japanese Yen	0.025	0.002	99.810	0.151	0.011	0.190
Australian Dollar	8.941	16.295	0.051	66.778	7.935	33.222
Swiss Franc	0.413	36.613	0.012	6.699	56.263	43.737
Contribution to Others	11.463	56.363	0.105	30.728	42.280	140.939
Contribution including own	95.998	108.037	99.915	97.506	98.543	
Net Spillover	-4.002	8.037	-0.085	-2.494	-1.457	Spillover Index 28.188%

Notes: Values reported are the variance decomposition based on 10-step ahead forecasts. The VAR lag length of order 1 was selected by the Hannan-Quinn Criterion.

Table 10: South African Rand

To	From					
	South African Rand	Euro	Japanese Yen	Australian Dollar	Swiss Franc	Contribution From Others
South African Rand	67.614	10.220	0.025	17.419	4.722	32.386
Euro	7.367	48.882	0.001	11.937	31.813	51.118
Japanese Yen	0.012	0.002	99.824	0.151	0.011	0.176
Australian Dollar	15.904	15.072	0.047	61.623	7.355	38.377
Swiss Franc	3.786	35.347	0.011	6.500	54.355	45.645
Contribution to Others	27.069	60.642	0.084	36.007	43.900	167.702
Contribution including own	94.683	109.524	99.908	97.630	98.255	
Net Spillover	-5.317	9.524	-0.092	-2.37	-1.745	Spillover Index 33.540%

Notes: Values reported are the variance decomposition based on 10-step ahead forecasts. The VAR lag length of order 1 was selected by the Hannan-Quinn Criterion.

A number of interesting results appear in the tables. In all the cases, the own market volatility spillover is highest with the diagonal elements having higher values as compared to off-diagonal elements. In case of Indian Rupee, Brazilian Real and South African Rand, the highest spillover is from Australian Dollar followed by Euro, Swiss Franc and Japanese Yen whereas in case of Chinese Yuan, the highest spillover is from Euro followed by Australian Dollar, Swiss Franc and Japanese Yen. So it can be inferred that Australian Dollar is the dominant currency in volatility transmission to the Indian, Brazilian and South African markets and Euro is the dominant currency in volatility transmission to Chinese markets. It is also observed from the table that all the emerging markets pass on maximum volatility to Australian Dollar succeeded by Euro, Swiss Franc and Japanese Yen. The estimates of the table above further strengthen the discussion.

According to the ‘contribution to others’ row and ‘contribution from others’ column, the emerging markets show similar picture. All the emerging foreign exchange markets contribute less and absorb more volatility from the developed markets. The ensuing figures of ‘contribution to others’ row for Indian Rupee, Chinese Yuan, Brazilian Real and South African Rand are 7.700, 0.920, 11.463 and 27.069 and ‘contribution from others’ are 11.151, 3.951, 15.465 and

32.386. These statistics disclose that the emerging markets are net receiver of volatility while the developed markets are net transmitter of volatility.

Furthermore it is also revealed from the corresponding table that the spillover index is highest for South African Rand followed by Brazilian Real, Indian Rupee and Chinese Yuan. This result corroborate the finding that variance of South African Rand is higher. In fact, the examination of the full table at a glance and explicitly at the ‘contribution to others’ row and ‘contribution from others’ column reflects that the gross directional volatility spillover ‘to others’ and ‘from others’ is highest for Euro and lowest for Japanese Yen. Moreover the net volatility spillover row emulate that Euro is the dominant currency in transmission of volatility to other markets.

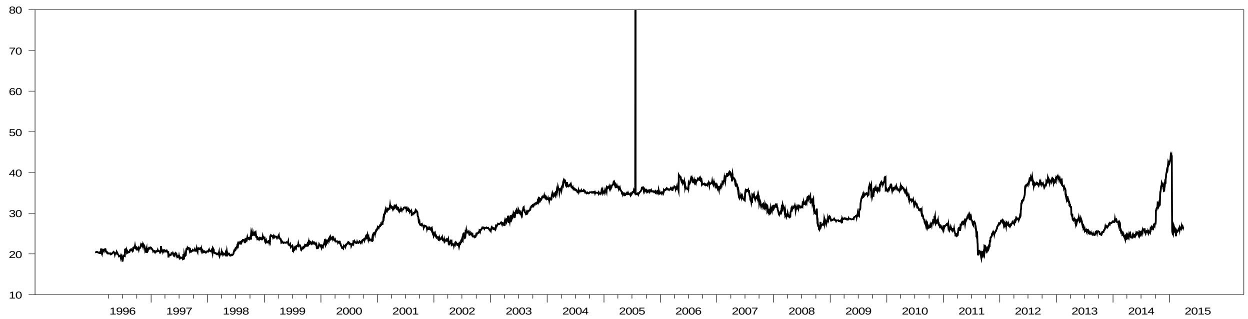
Although the spillover tables provide a summary of the average behaviour of the foreign exchange markets but it is likely to miss the impact of several crises or economic events that might have cropped up during the period of analysis. To deal with this issue, the volatility spillover is evaluated using 200-day rolling sample to suggest the enormity and character of the spillovers through the corresponding time series of the spillover indices.

Figure 5 depicts the total volatility spillover plots for the four emerging foreign exchange markets. This spillover graphs is a reaction to the economic events such as debt crisis, stock market crash, currency crisis etc. The figures show a gentle upward trend at the beginning but reached a peak during 2005, 2009, 2012 and 2014. This can be on account of the dollar crisis in 2005, the global financial crisis in 2008 and the Eurozone debt crisis in 2011. Even if the volatility spillover index is crucial, still it fails to produce a design regarding the directional spillover.

Figure 5: Total Volatility Spillover, 200-day Rolling Windows

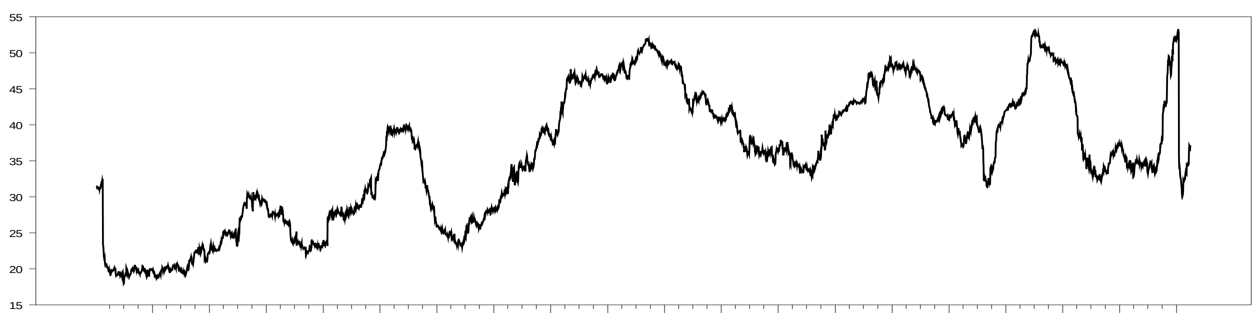
Indian Rupee

Chinese Yuan



Brazilian Real

South African Rand

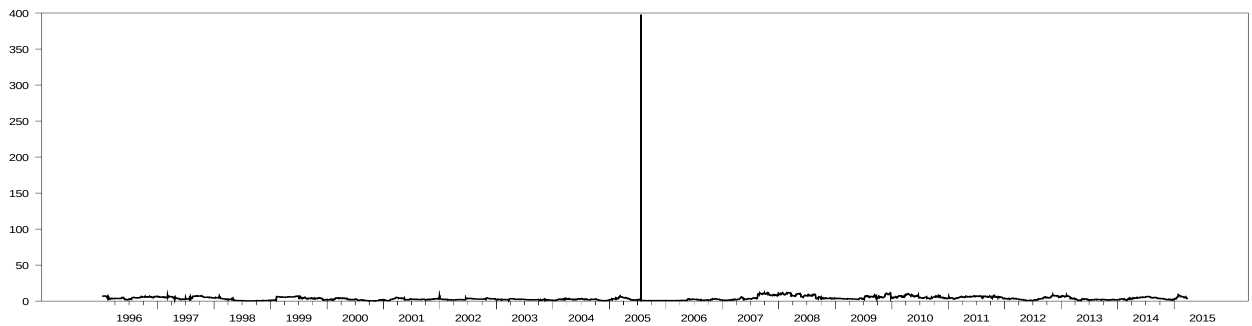


The directional spillover plots were obtained by estimating the aforesaid row and column using 200-day rolling sample. Figure 6 and figure 7 present the directional volatility spillover 'from others' and 'to others' for the four emerging foreign exchange markets. According to the figure, the directional spillovers 'from and to' is more definite and strong for South African Rand with Brazilian Real, Indian Rupee and Chinese Yuan securing the second, third and fourth position. The directional spillover varies significantly overtime and is responsive to the economic events.

Figure 6: From Four Emerging Markets, 200-day Rolling Windows

Indian Rupee

Chinese Yuan



Brazilian Rand

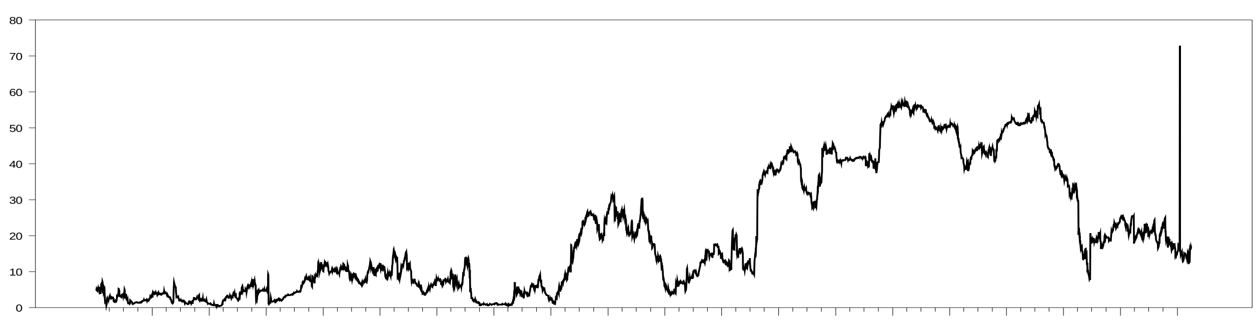
South African Rand

Figure 7: To Four Emerging Markets, 200-day Rolling Windows

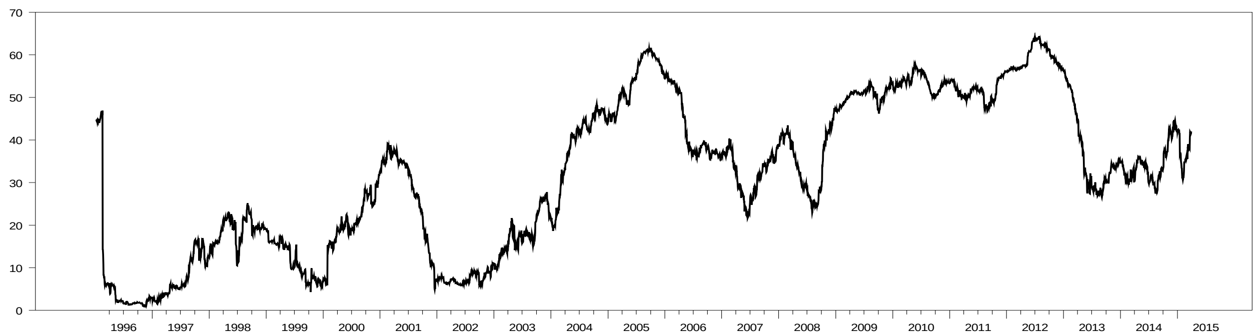
Indian Rupee

Chinese Yuan

Brazilian Real



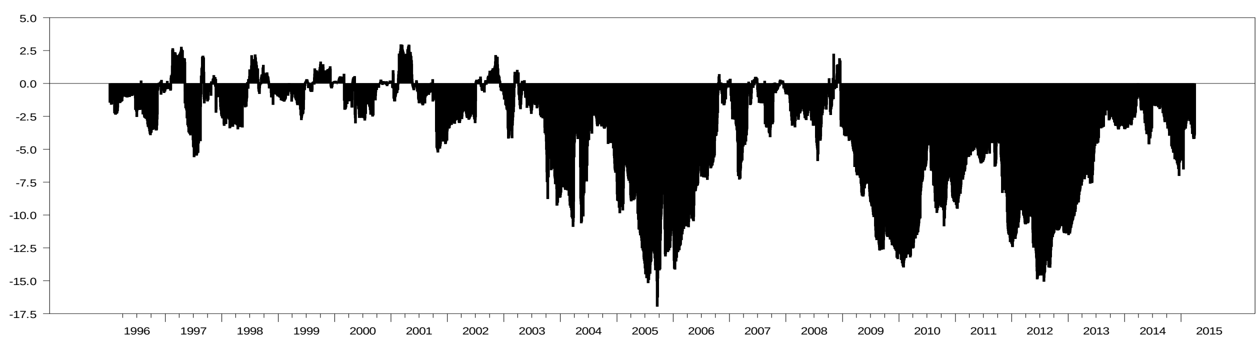
South African Rand



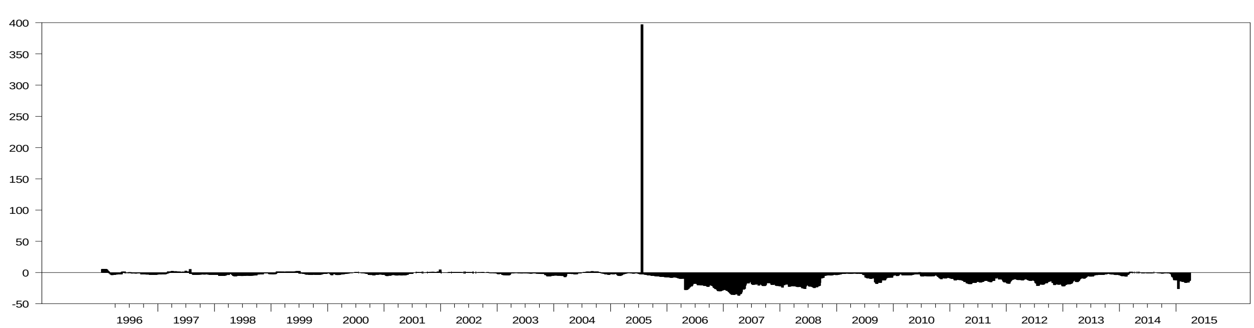
Finally, figure 8 and figure 9 displays the net volatility spillover and net pairwise volatility spillover of the four emerging foreign exchange markets which is obtained by estimating equation (10) and equation (11) using 200-day rolling sample. These figures suggest that the emerging economies are primarily net receiver of volatility. Among the emerging markets, South African Rand is the highest receiver of volatility, as is evident from the magnitude of spillover from developed economies. It is followed by Brazilian Real, Indian Rupee and Chinese Yuan. The figures also finds support from the volatility spillover tables, discussed earlier.

Figure 8: Net Volatility Spillover, 200-day Rolling Windows

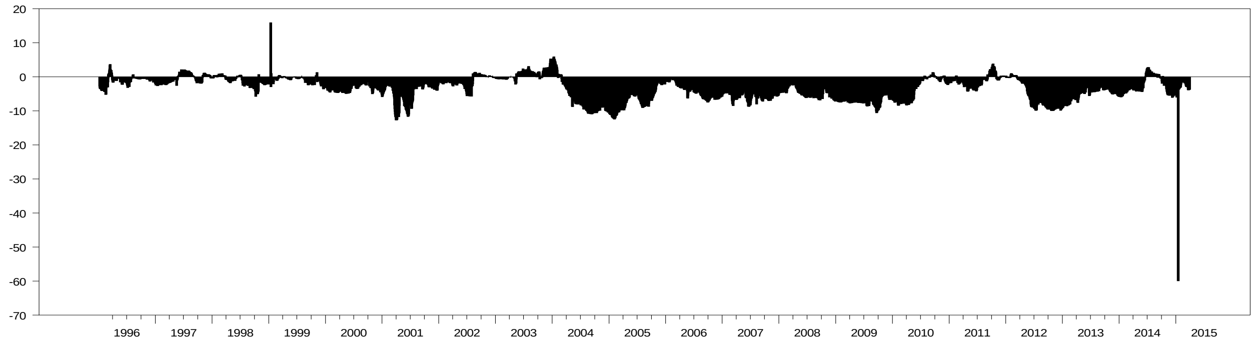
Indian Rupee



Chinese Yuan



Brazilian Real



South African Rand

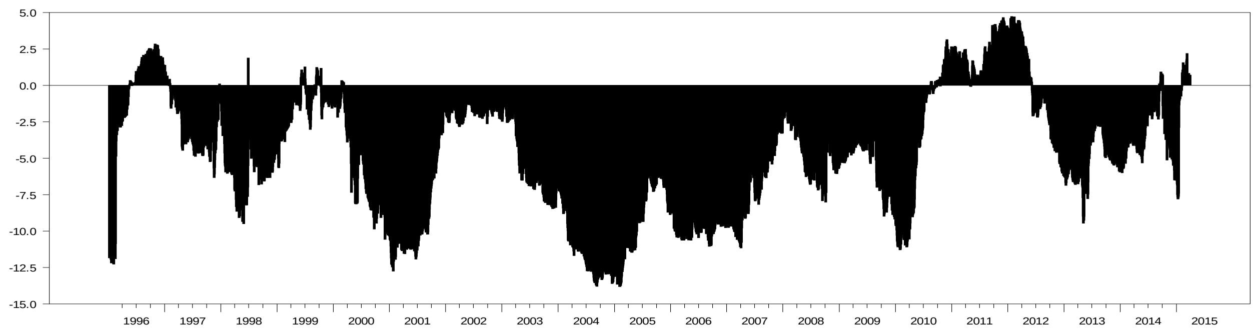
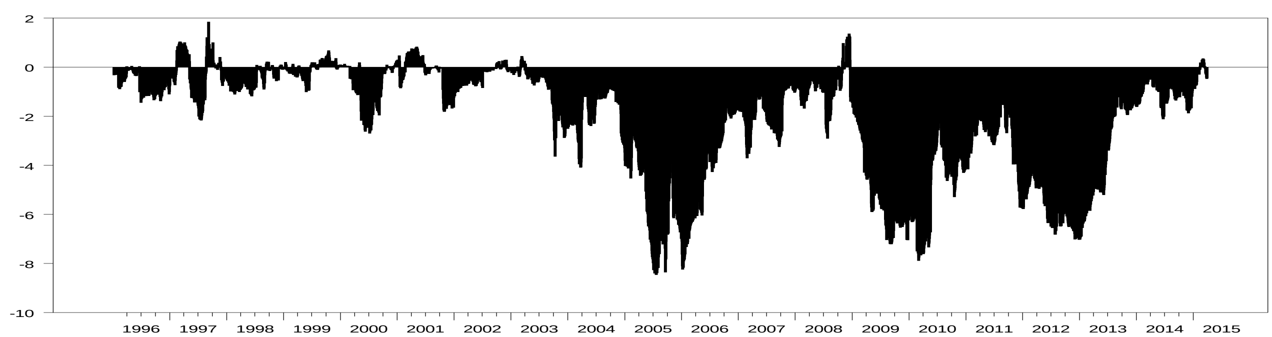
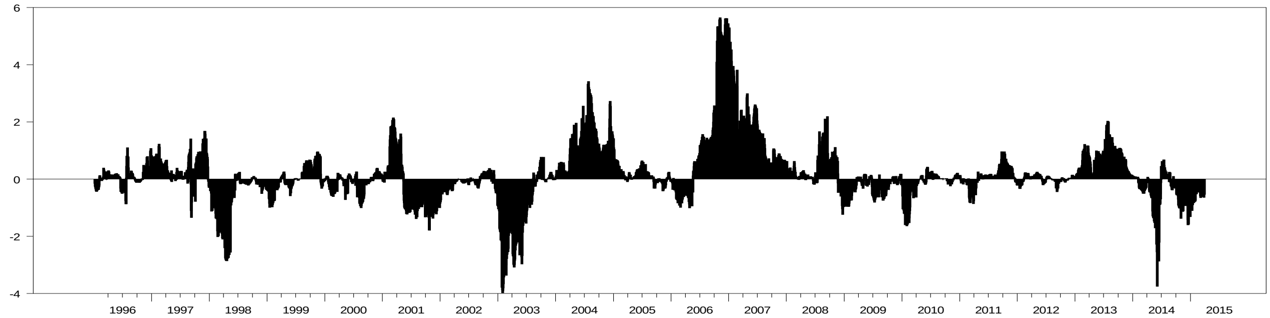


Figure 9: Net-Pairwise Volatility Spillover, 200-day Rolling Windows

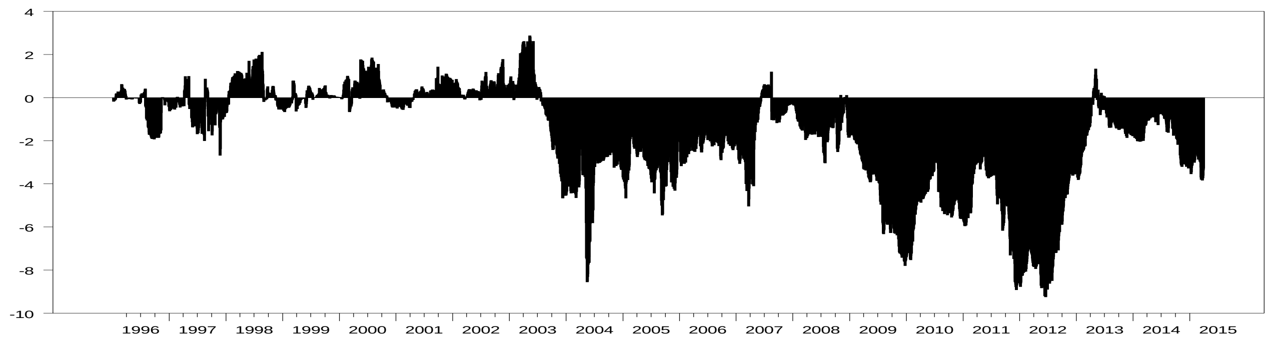
India-Euro



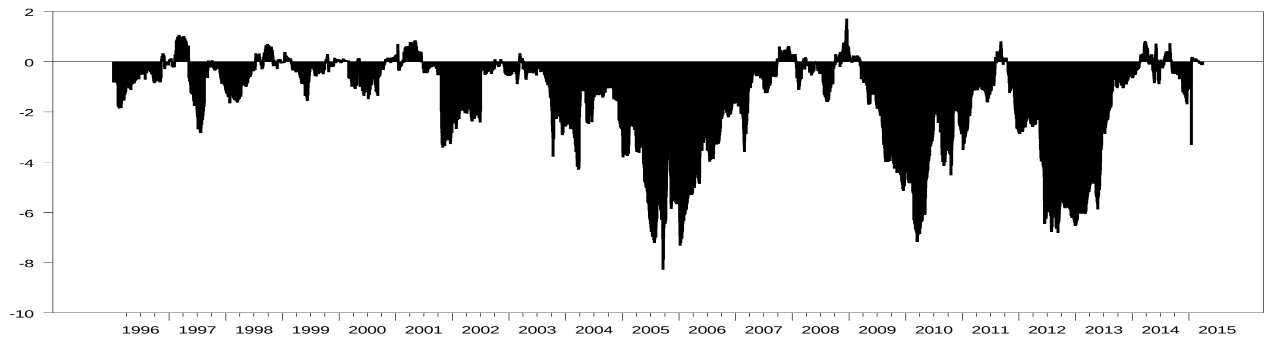
India-Japanese Yen



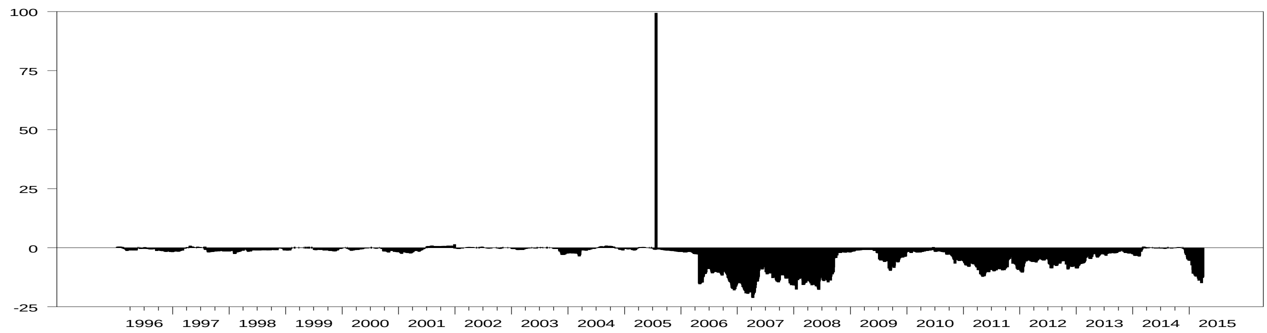
India-Australian Dollar



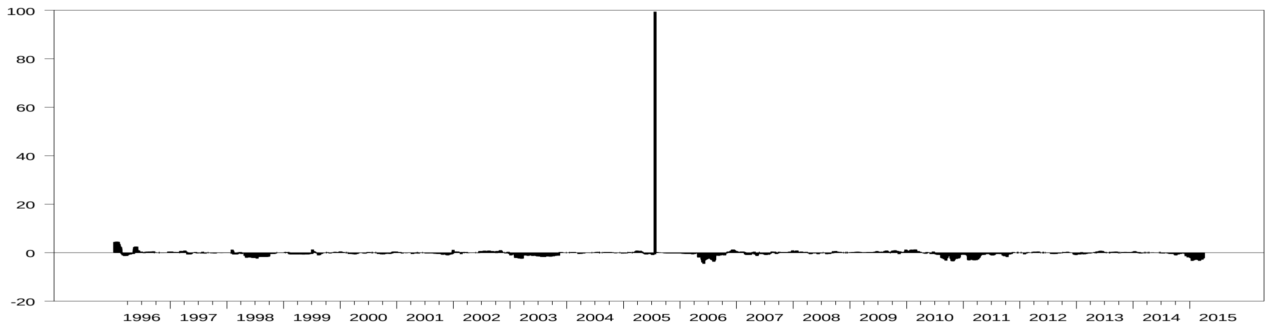
India-Swiss Franc



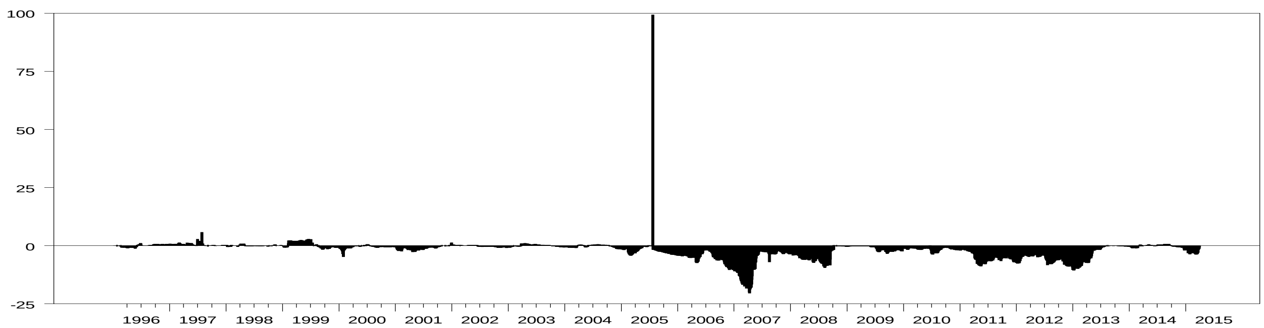
China-Euro



China-Japanese Yen



China- Australian Dollar



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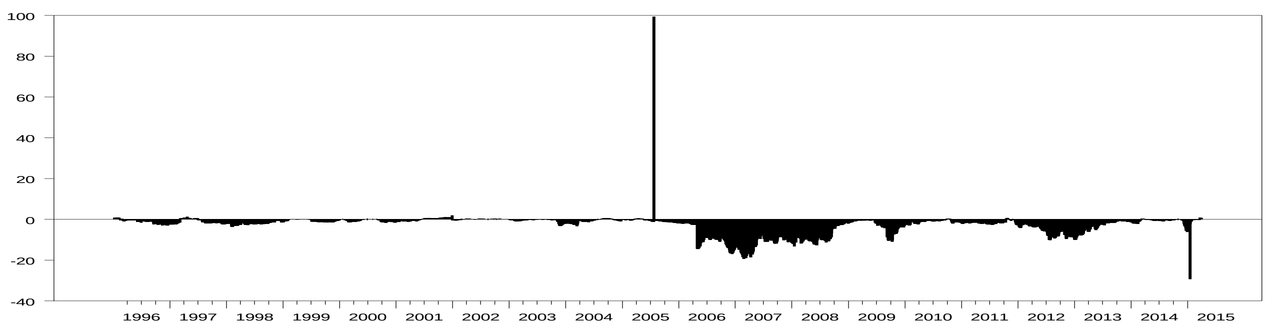
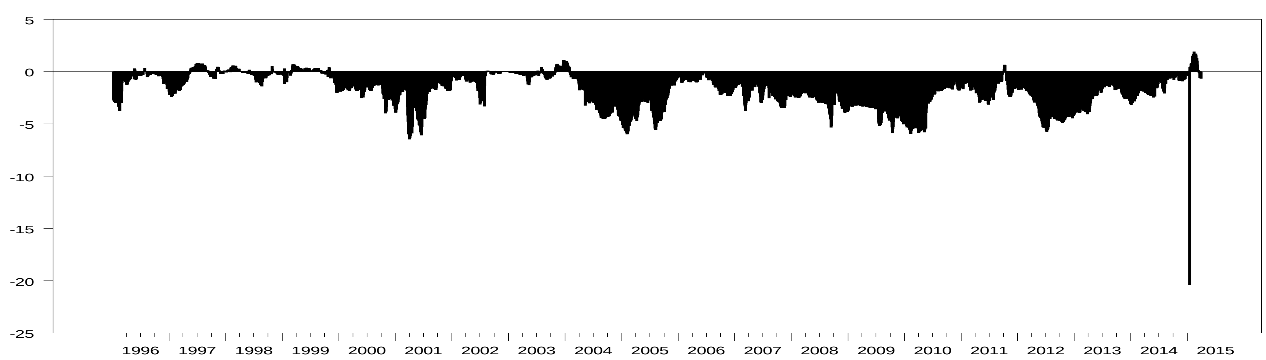


Brazil-Euro



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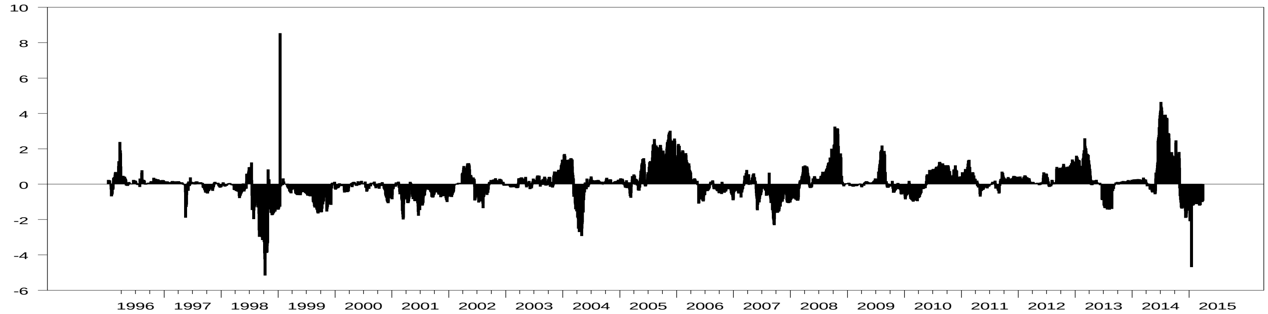

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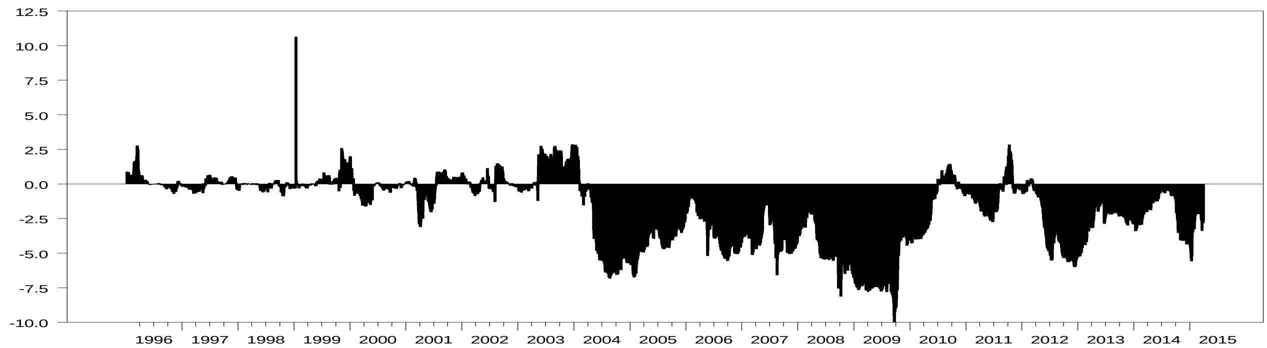

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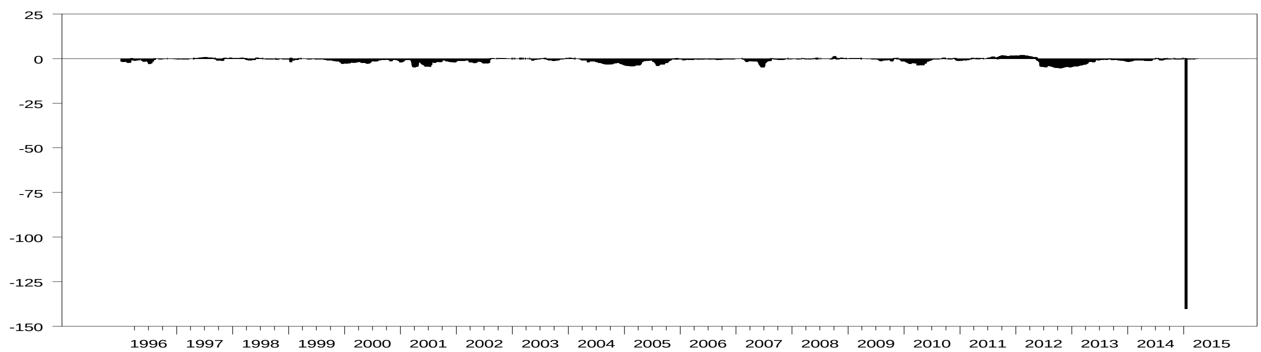
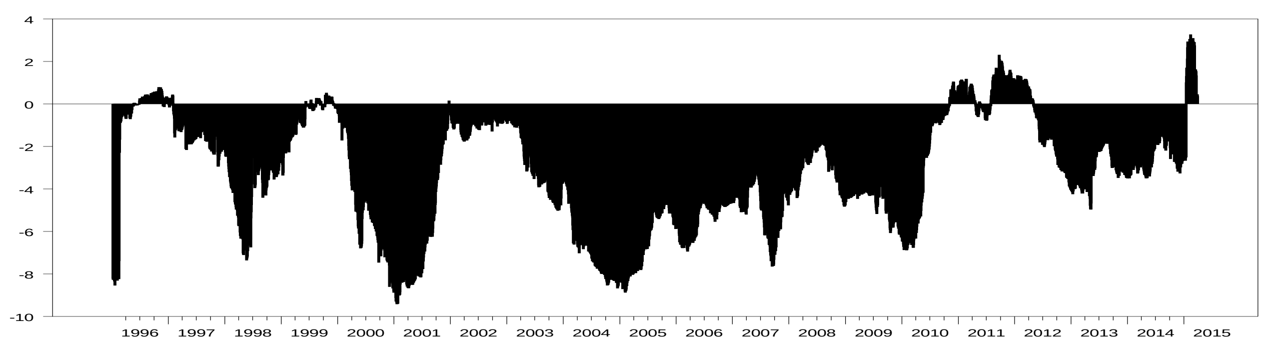


South Africa-Euro



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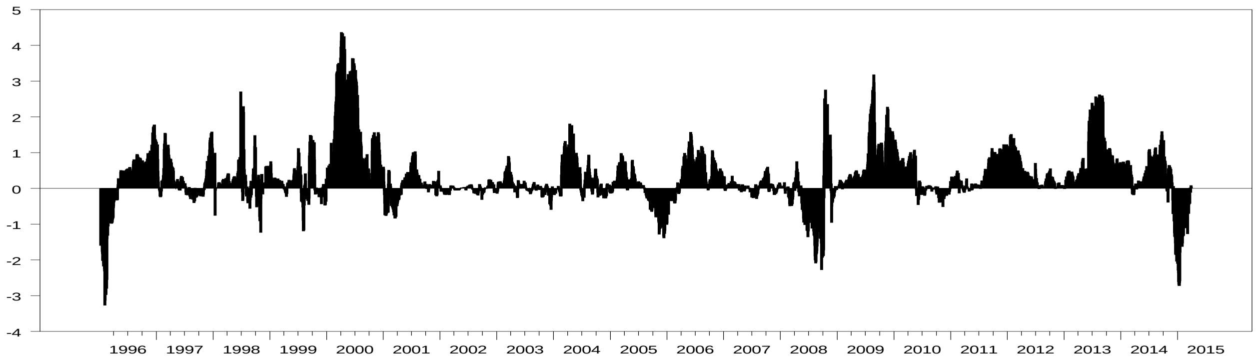

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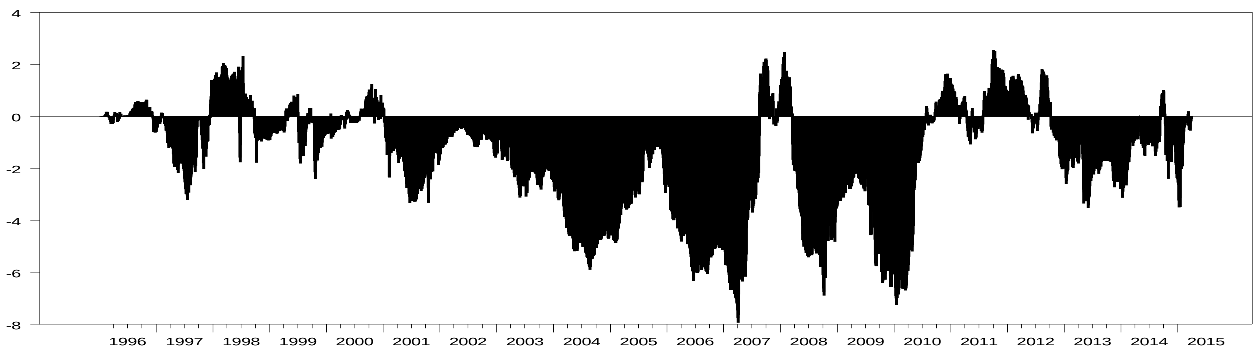

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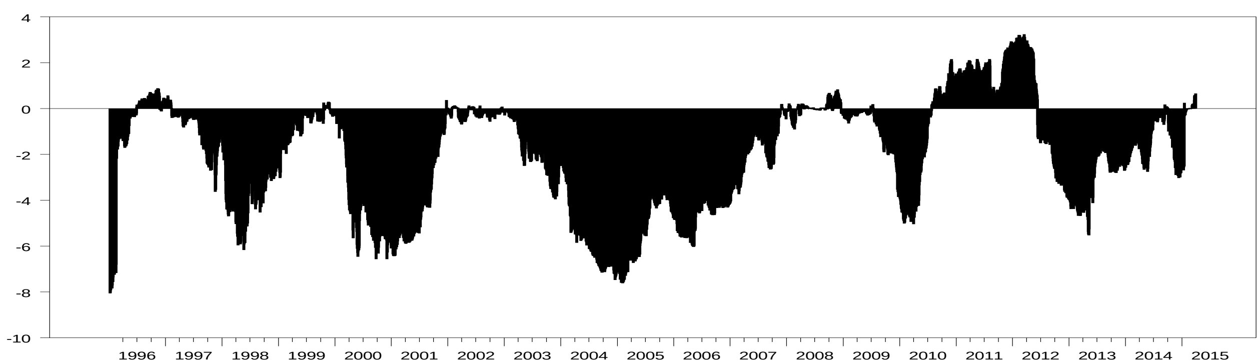

5. CONCLUSION AND POLICY IMPLICATION

This paper has investigated the return co-movement and volatility spillover among the emerging market economies and the developed economies. To recapitulate, exchange rate is one of the critical variables that occupy a central position in policy proposals and whose stability is considered as one of the most important parameters in achieving high economic growth. Ever since the exchange rate became market determined, the pattern of volatility has undergone a distinct change and the possibility of such volatility transmission had multiplied. The period from 2000 onwards witnessed sustained volatility in the exchange rate of developing economies. This necessitated a detailed econometric analysis of the return co-movement and volatility spillover.

The econometric analysis had set out in identifying that most of the emerging foreign exchange markets are explosive in nature as compared to the developed economies. It is also inferred from the analysis that Indian Rupee, Chinese Yuan, Brazilian Real and South African Rand are more influenced by Euro, Australian Dollar and Swiss Franc. Apart from this it is also revealed from the study that emerging foreign exchange markets are net receiver of volatility and developed markets are net transmitter of volatility. The investigation further propounds that among other emerging markets, South African Rand is the highest receiver of volatility. This proposition is further supported by the statistics in the spillover index and the graphs of the 200-day rolling sample. Nonetheless, dynamic correlations and volatility spillovers show large variability and are positively associated with extreme economic episodes, such as during the global recession.

Finally these results paved the path for the central banks of the emerging market economies to concentrate more on proper policy formulations to restore peace and tranquility in the foreign exchange markets as investors decide on portfolio diversification and risk management largely on the basis of the prevailing conditions in the foreign exchange markets.

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