An investigation of price discovery and volatility spillovers in India's currency futures market

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Abstract

This paper investigates the price discovery and volatility spillovers between spot and futures prices of four major international currencies traded on two trading platforms in India. The price discovery results confirm the long-run equilibrium relationship between spot and future prices of sample currencies even after accounting for structural break in each currency series. The results of volatility spillovers under MGARCH framework indicate the presence of short and long-run volatility spillovers between futures and spot markets. Volatility spillovers are stronger from futures to spot in short-run while inverse is found in the long-run. Several market implications are analysed and discussed.

Keywords: Currency futures market; Price discovery, cointegration, volatility spillovers, BEKK-GARCH, DCC-GARCH

JEL classification: G12, G13, C32

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1. Introduction

Over the past years, several inquiries have explored the special role of price discovery and volatility spillovers in informationally efficient futures market. Price discovery implies the short and long-run relationship between futures and spot markets.[2] Under cointegration framework, price discovery indicates the existence of long-run equilibrium relationship between futures and cash markets. If departure from equilibrium occurs, prices in one of these markets should adjust to correct the disparity (see e.g., Zhong et al, 2004). Apart from price discovery, volatility is also an important source of information, which helps in examining the process through which the volatility in one market affects that of another market. It has strong implications for market participants especially with regard to information transmission between futures and spot and between futures prices of trading platforms. When volatility spillover moves strongly from futures to spot market, it is inferred that the futures market impounds market information more quickly than spot and hence such market is characterized as the market for speculators and vice-versa for hedgers. Several factors are generally considered responsible for price discovery and volatility spillover processes such as liquidity, transaction costs, and other regulatory restrictions (short-selling restrictions).

The present study attempts to add value to the existing literature by examining the price discovery and volatility spillovers in spot and futures prices of four currencies (viz., USD/INR, EURO/INR, GBP/INR and JPY/INR*)* and between futures prices of both stock exchanges viz., Multi-Commodity Stock Exchange (MCX-SX) and National Stock Exchange (NSE) in India, during 2010-12 (till February), the period that witnessed the most radical

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[2] Erik Theissen (2011) could be a good reference to understand the price discovery process in detail.

changes in both the practice of and policy debates on the introduction of currency futures trading in the country.[3]

In the literature, numerous studies have examined price discovery and volatility spillover process covering equity and commodity markets (see e.g., Y. Tse, 1999; Fung, Leung and Xu, 2001; Roope and Zurbruegg, 2002; Fung, Leung and Xu, 2003; Xu and Fung, 2005; Hua and Chen, 2007; Mandaci and Torun, 2007; Ge, Wang and Ahn, 2008; Kao and Wan, 2009; Mahalik, Acharya and Babu, 2009; Karmakar,2009; Kasman et al.,2009; Kenourigios and Samitas, 2011, Kumar and Pandey, 2011; Du, Yu and Hayes, 2011; Liu and An, 2011). But there are very limited studies that have covered the currency futures market. The reason could be because the currency futures market is a recent development in most of the mature and emerging countries. However, in a recent study, the price discovery process in currency market is highlighted by the study of Osler et al. (2011) who examined the price discovery process by exhibiting the incorporation of new information into exchange rate dynamics. Some studies such as Crain and Lee (1995), Chatrath and Song (1998) and Chen and Gau (2010)[4] have also analysed the impact of news announcements on foreign exchange market volatility. Their study broadly concluded that on announcement day, volatility spillover moves stronger from futures to cash market. Studies have also highlighted on the role of futures market in price discovery by exhibiting whether futures market contributes more in price discovery than spot market or not. In this regard, studies of Martens and Kofman (1998), Rosenberg and Traub (2009), and Tse et al. (2006) reveal that the futures market contributes more to price discovery than does the spot in currency market. While, Lyons

[3] Both trading platforms account for almost 90% of trading volumes in currencies.

[4] The study of Chen and Gau (2010) provides very good literature review on various studies which can be further referred to understand the price discovery and volatility spillovers in currency market. Due to space constraints we abstain from further elaboration.

(2001) emphasized more on the role of spot market in price discovery than futures market because spot market enjoys stronger active trading and higher liquidity in currency market.

Considering the Indian case, no study has so far been carried out to investigate the price discovery and volatility spillovers in currency market. This could be due to its recent origin and smaller size of the market. Therefore, this study attempts to examine the price discovery and volatility spillovers in India's currency futures markets. In a recent study, Bahera (2011) has examined the onshore and offshore market of Indian rupee in the light of volatility and shock spillover. Using multivariate GARCH model, his study exhibited the onshore-offshore linkages of the Indian rupee and concluded that there is no mean spillover impact of non-deliverable forward (NDF) on onshore spot, whereas, shocks and volatilities in NDF do influence the onshore rupee markets. Somnath (2011) examines the relationship between currency futures and exchange rate volatility in India. The study used the data of USD/INR futures from NSE for the period starting from 02 April 2007 to 11 February 2011. Using Granger causality, the study showed that there is a two-way causality between the volatility in the spot exchange rate and trading activity in the currency futures market. Both studies have strong policy implications but the objectives of these studies were different from the present work as this study not only provides the evidence of price discovery and volatility spillovers in spot and futures markets but also examine the cross market linkages with the use of recent data. At least two features distinguish our analysis in this paper. First, to the best of our knowledge, this study is a first attempt to incorporate the role of regime shifts in the process of price discovery by applying the recently developed techniques of structural break and cointegration with regime shifts in case of India. The identification of structural break is important because it helps the policy makers and practitioners to infer on the major upheavals in currency market.[5] Second, in order to avoid the possible omission-of-variable biases in the conditional first- and second-moments a family of Multivariate GARCH (henceforth, MGARCH) models is used to exhibit the short and long-term volatility spillovers in currency markets of India. This is new to the existing literature currency markets in case of India.

The remainder of this study is organized as follows: section II provides an overview of Indian currency market, section III explains the methodology, section IV shows data and summary statistics, and section V provides empirical results followed by section VI contains concluding remarks and policy suggestions.

2. An overview of India's currency market

In India, the development of currency derivatives market is a recent phenomenon as it started in 2008. Two historical developments are generally considered responsible for the development of currency derivative market in India. Firstly, due to the reform measures undertaken during 1990s which initiated the process of structural change in Indian currency market. In 1993, India adopted the fully floated exchange rate which played significant role in the implementation of total current account convertibility. Secondly, there was late realization to enhance the outreach of Indian rupee internationally. A currency futures market was set-up in 2008 under the custodianship of Reserve Bank of India (RBI) and Security and Exchange Board of India (SEBI). Reserved Bank of India controls the currency market in the country and intervenes as when required to address the excess volatility in the market, while ensuring the market based determination of exchange rates. Currency futures trading in INR-US dollar started on August 29, 2008. Exchange-traded currency futures have now been expanded to the euro, pound and yen pairing. At present, currency futures contracts are traded

[5] Ramprasad Bhar (2001) in his study used these approaches to exhibit the return and volatility dynamics in the spot and futures market in case of Australia. The paper discusses briefly about these tests.

on four exchanges in India viz., MCX-SX, NSE, BSE (Bombay Stock Exchange) and United Stock Exchange (USE). It may be noted that currency derivatives trading takes place on stock exchanges and hence this market is regulated by SEBI, which is also the stock market regulator in India.

The present study has also strong implications for India's currency market especially at the time when the economy is feeling the heat of recent European upheavals which has hurt the growth prospect considerably. The grim macroeconomic outlook caused by drying up of foreign capital inflows, increase in fiscal and trade deficits and rise in oil prices, several questions have been raised on the sustainability of high growth rate of the economy. Recently, the currency market came under pressure due to fear of late recovery of USA and the troubled European countries. The price upheavals in energy products coupled with domestic food inflation have also putted downward pressure on Indian rupee which as a result depreciated at historical low level and is currently under great strain. The Indian government with the help of central bank is trying to stabilize the macroeconomic scenario and especially the volatile foreign exchange market. Therefore, it is critically important that one should provide the recent evidence of price discovery and volatility spillovers between OTC and futures exchange derivatives market.

Given the state of currency market, following are the major objectives of the study:

1. Whether the futures prices recorded on NSE and the corresponding spot prices exhibit price discovery and volatility spillover process;

2. Whether similar information linkages are observed between currency futures prices on MCX-SX and spot prices;

3. Are there any linkages between currency futures prices recorded on two trading platforms under study?

3. Methodology

3.1. Process of price discovery and cointegration

At first stage, stationarity condition using conventional methods of unit root tests viz., Augmented Dickey Fuller (ADF) and Phillips and Perron (PP) has been checked for all currencies under consideration, followed by structural break unit root test in order to find out for the occurrence of any abnormal events. For this purpose, Andrew-Zivot (AZ, 1992) unit root test with structural break (see for details, John et al. 2007) has been employed.[6] Since conventional cointegration tests, such as Engle and Granger (EG) and Johansen Juselius, are not applicable to exhibit the long-run relationship especially when structural breaks are present in both series. Therefore, the contemporary econometric technique of Gregory and Hansen (GH, 1996) cointegration test is used to exhibit the long-run relationship (see for details, Steven Cook, 2005).[7] According to GH test, in the presence of regime shifts and structural break, the power of EG test gets reduced substantially. Therefore, GH test under EG framework allows identifying the breaks in either the intercept or the intercept and co-integrating coefficient between two variables endogenously.

The results of GH (1996) are further confirmed by the Johansen cointegration (1988, 1991) test and Vector Error Correction Model (VECM) as mentioned in equation 5 and 6. The bivariate co-integrated series $P_t = (F_t, S_t)'$, is represented by a vector error correction model (VECM):

$$\Delta F_t = b_1 + \delta_1 ECT_{t-1} + \sum_{i=1}^{k} d_{1i} \Delta F_{t-i} + \sum_{i=1}^{k} g_{1i} \Delta S_{t-i} + \varepsilon_{1t} \ldots\ldots\ldots (1)$$

[6] This study provides a detailed review of unit root tests with structural break.

[7] The study provides a detailed explanation of different variants of cointegration model.

$$\Delta S_t = b_2 + \delta_2 ECT_{t-1} + \sum_{i=1}^{k} d_{2i} \Delta F_{t-i} + \sum_{i=1}^{k} g_{2i} \Delta S_{t-i} + \varepsilon_{2t} \ldots\ldots\ldots (2)$$

Where $ECT_{t-1} = F_{t-1} - S_{t-1}$ is the error correction term.

Given the large number of parameters that would have to be estimated in the spillover model (discussed in subsection in 3.2), a two-step procedure similar to that implemented by Bekaert and Harvey (1997), Ng (2000), and Baele (2005) has been considered in this study. In the first step, the vector error correction model is estimated to obtain estimates of the shock vector for cash and futures prices. In the second step, the first stage estimates are used as data to check for volatility spillover between spot and futures prices and between the futures prices of both markets.

3.2. Process of volatility spillovers

Numerous studies have investigated the process of volatility spillover to exhibit the spread of news from one market that affects the volatility process of another market. See, for instance, Hamao, Masulis and Ng (1990), Koutmos and Booth (1995), and Lin, Engle and Ito (1994) for US, UK and Japanese Stock markets and Booth, Martikainen and Tse (1997) and Christofi and Pericli (1999) in other international stock markets. Most studies in the literature have used different variants of GARCH models to exhibit the volatility spillovers between markets. Engle et al (1990) introduced the GARCH models to examine the volatility spillovers. According to Chan, Chan and Karolyi (1991), it is the volatility which determines the flow of information from one market to another and not just the simple price change. [8]

In this paper, three different variants of multivariate GARCH models (BEKK, Constant Conditional Correlation (CCC), and Dynamic Conditional Correlation (DCC)) are used to

[8] For further details, Chan, Chan and Karolyi (1991) could be a good reference on the need to study the volatility spillovers.

model the volatility spillover dynamics between the spot and futures prices of four currencies traded on MCX-SX and NSE platforms. The BEKK model is used as a benchmark to examine the volatility spillovers. The other models (CCC and DCC) are used to substantiate the BEKK results under VARMA-GARCH (Ling and McAleer, 2003) framework. This approach to modelling the conditional variances allows large shocks to one variable to affect the variances of the other variables. Under this approach, the variance terms take the form of (for a 1, 1 model):

$$H_{ii}(t) = \phi_{ii} + \sum_j \alpha_{ij}\varepsilon_j(t-1)^2 + \sum_j \beta_{ij}H_{jj}(t-1) \; \ldots\ldots (3)$$

This is mainly used to show the impact of large shocks in one variable on the variance of the others. This is a convenient specification which allows for volatility spillovers (see Sadorsky,2012). In the first step, univariate GARCH models are used to estimate the variances. In the second step, correlations are modelled based on the standardized residuals from step one. A brief introduction of BEKK, CCC and DCC are explained below:

3.2.1. GARCH (BEKK) model

It is also known as BEKK, suggested by Baba, Engle, Kraft and Kroner (1990). In fact, it is the most natural way to deal with the multivariate matrix operations. The BEKK specification takes the following form:

$$H_t = A_0'A_0 + A_i'\varepsilon_{t-i}\varepsilon_{t-i}'A_i + B_j'H_{t-j}B_j \; \ldots (4)$$

Where A_0 is a symmetric $(N \times N)$ parameter matrix, and A_i and B_j are unrestricted $(N \times N)$ parameter matrices. The important feature of this specification is that it builds sufficient generality, allowing the conditional variances and covariances of the time-series to influence each other, and at the same time, doesnot require estimating a large number of parameters. In the bivariate system with $p=q=1$, equation (7) becomes:

$$
\begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \begin{bmatrix} \alpha_{11,0} & \alpha_{12,0} \\ \alpha_{21,0} & \alpha_{22,0} \end{bmatrix} + \begin{bmatrix} \alpha_{11,1} & \alpha_{12,1} \\ \alpha_{21,1} & \alpha_{22,1} \end{bmatrix}' \begin{bmatrix} \varepsilon^2{}_{1,t-1} & \varepsilon_{1,t-1}, \varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}, \varepsilon_{2,t-1} & \varepsilon^2{}_{22,1} \end{bmatrix} \begin{bmatrix} \alpha_{11,1} & \alpha_{12,1} \\ \alpha_{21,1} & \alpha_{22,1} \end{bmatrix}
+ \begin{bmatrix} \beta_{11,1} & \beta_{12,1} \\ \beta_{21,1} & \beta_{22,1} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} \beta_{11,1} & \beta_{12,1} \\ \beta_{21,1} & \beta_{22,1} \end{bmatrix} \quad (5)
$$

Where, the $\alpha_{11,1}$ and $\alpha_{22,1}$ represent the effect of the stock on the futures uncertainty of the same time-series and $\alpha_{21,1}$ and $\alpha_{12,1}$ represent the cross effect i.e. the effects of the shock of the second series on the futures uncertainty of the first series and vice-versa. Therefore, this model specification is appropriately fitted to investigate volatility spillovers between two financial assets (see for details, Pejie Wang, 2009).

3.2.2. Constant Conditional Correlation (CCC) model:

A constant correlation means that the correlation coefficient is constant over time or it is not a function of time.

$$
\frac{h_{12t}}{\sqrt{h_{11t}h_{22t}}} = \rho \quad \dots (6)
$$

Therefore, h_{12t} is decided as:

$$
h_{12t} = \rho\sqrt{h_{11t}h_{22t}}
$$

An obvious advantage in the constant correlation specification is simplicity. Nonetheless, it can only establish a link between the two uncertainties, failing to tell the directions of volatility spillovers between the two sources of uncertainty.

3.2.3. Dynamic Conditional Correlation (DCC):

The Engle (2002) dynamic conditional correlation model is estimated in two steps. In the first step, GARCH parameters are estimated. In the second steps correlations are estimated.

$$H_t = D_t R_t D_t \quad \ldots\ldots (7)$$

In equation 10, H_t is the 3×3 conditional covariance matrix as in our case, R_t is the conditional correlation matrix and D_t is a diagonal matrix with time-varying standard deviations on the diagonal.

$$D_t = diag(h_{11t}{}^{1/2} \ldots\ldots h_{33t}{}^{1/2})$$

$$R_t = diag(q_{11t}{}^{-1/2} \ldots\ldots q_{33t}{}^{-1/2}) Q_t diag(q_{11t}{}^{-1/2} \ldots\ldots q_{33t}{}^{-1/2})$$

Where Q_t is a symmetric positive definite matrix:

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 \varepsilon_{t-1} \varepsilon'_{t-1} + \theta_2 Q_{t-1} \quad \ldots.. (8)$$

$\overline{Q}$ is the 3×3 unconditional correlation matrix of the standardized residuals ε_{it}. The parameters θ_1 and θ_2 are non-negative with a sum of less than unity.

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}} \quad \ldots\ldots (9)$$

The MGARCH models are estimated by Quasi-Maximum Likelihood Estimation (QMLE) using the BFGS algorithm. T statistics are calculated using a robust estimate of the covariance matrix (Sadorsky, 2012).

4. Data Description

The sample data for the daily futures prices of four currencies viz., USD (US Dollar/INR), EURO (Euro/INR), GBP/INR (British Pound/INR) and JPY/INR (Japanese Yen/INR) is collected from MCX-SX and NSE websites (www.nseindia.com, www.mcxindia.com). The spot prices are collected from Reserve Bank of India (RBI). All closing prices of futures series are taken for the nearest contract to maturity. The study covers the sample period from

February 01, 2010 to February 29, 2012 (481 observations). For estimation purposes, all price series have been converted into natural logarithms. While estimating the model and due to ease of better understanding, following notations have been used for all sample currencies: SEURO (Spot Euro), SUSD (Spot US dollar/INR), SGBP (British Pound/INR), SJPY (Japanese Yen/INR), EURONSE (Euro Futures traded at NSE), EUROMCX (Euro Futures traded at MCX-SX), JPYNSE (Japanese Yen Futures traded at NSE), JPYMCX (Japanese Yen Futures traded at MCX-SX), GBPNSE (British Pound Futures traded at NSE), GBPMCX (British Pound Futures traded at MCX-SX), USDNSE (US Dollar Futures traded at NSE) and USDMCX (US Dollar Futures traded at NSE).

5. Empirical Results

The empirical results start with descriptive statistics for sample currencies (spot and futures market) as shown in Table 1. The mean returns of all four currencies are almost zero percent. The highest mean daily returns is observed in case of Japanese futures (JPYNSE and JPYMCX) and spot returns (SJPY) which is 0.16 percent and lowest in case of Euro spot and futures which is 0.002 percent. While, the range of daily returns among these four currencies is highest for Euro futures (EURONSE) with the lowest and highest values of -4.07 percent and 4.27 percent, respectively. The standard deviation as a measure of volatility is highest for spot euro (SEURO) followed by futures of Japanese Yan (JPYMCX and JPYNSE) and Euro (EUROMCX and EURONSE) for both futures exchanges. In general, the risk-returns relationship is positive for all foreign exchange series. The volatility measures are almost eighteen times larger than the mean values. While, the Japanese Yen (JPY) and the US dollar (USD) spot and futures returns series exhibit negative skewness, the GBP and EURO returns series show positive skewness, all returns series are leptokurtic and violate normality as exhibited by Jarque-Bera (JB) statistics. The results imply that the market is not informationally efficient for the sample currencies. Ljung Box (LB) test confirms no autocorrelation in sample series up to 10 lags with exception of EUROMCX, EURONSE and SEURO.

[Insert Table 1 about here]

5.1. Tests of stationarity and price discovery process

Stationarity conditions of the currency futures-spot price series expressed in logarithmic form are tested by conventional ADF and PP. ADF and PP tests confirms the existence of unit root at level and achieves stationarity at first difference for all currency series. [9] It may be noted that the ADF and PP tests may be suspect when the sample period under analysis may have witnessed major events (currency devaluation, economic and trade crisis, regulatory shocks etc.), which are likely to create structural breaks in the series. In order to account for any possible regime shifts resulting from structural break, Andrew-Zivot unit root test has been implemented on sample currency series. The results are shown in Table 2. The estimated results indicate that the structural break date of EURO (spot and futures) coincides with JPY (spot and futures) on both platforms, which occurs on 30-08-2010. The results imply that both trading exchanges and spot market moves in the same manner and impact of any major events are realized at the same time. The structural break dates for US dollar futures (USDNSE and USDMCX) and its spot (SUSD) is on 24-05-2010. Similarly, matching structural break date is found for GBP futures (GBPNSE and GBPMCX) and its spot (SGBP), which is on 25-05-2010. The results have important implications from the point of view of market efficiency, as they indicate that there is not much noise in the trading of futures and spot on both exchanges and there is also symmetry in the flow of information

[9] Unit root results are available upon request.

between both markets. At the same time, it must be noted that except EURO and JPY, the other two currencies viz., USD and GBP exhibit different dates of structural break which require further macroeconomic analysis.

[Insert Table 2 about here]

[Insert Table 3 & 4 about here]

The GH test has been used to exhibit the long-run relationship with regime shifts which accounts for endogenous identification of structural break in the variables. This is relevant in order to perform the rigorous cointegration analysis especially when external shocks or policy shift/reversal are assumed in the model.

The GH test provides following structural break dates for sample currency series as shown in Table 3&4. The structural break dates provided by AZ and GH tests don't seem to match and hence this requires further attention. The reason could be because AZ test identifies the structural break in series at level while EG based GH cointegration show structural break dates on residuals obtained from the estimated series. It may here be noted that these tests identity one structural break for each sample series. While, there is a possibility that time-series of exchange rates might have witnessed multiple structural breaks over the study period. Hence, Bai-Perron (BP, 2003) structural break test is implemented which identifies multiple regime shifts in the data. The results are shown in Table 5. The observed date discrepancies can be reconciled by the fact that all structural breaks identified by these models (AZ and GH) are captured by BP tests.

One must also keep in mind that in prior literature structural break tests are fitted on low frequency data and hence capturing structural break on daily data as in this case needs to be analysed rationally as these structural break tests may be more efficient in identifying a period say the month or the quarter rather than concluding on a single break date.

The study conducts the bivariate cointegration test between spot, futures MCX and futures NSE prices for the sample currencies using GH (1996) test. The results indicate that despite structural break in the data, there is long-run equilibrium relationship between futures and spot prices of all currencies (see Table 3).

[Insert Table 5 about here]

The results of GH test are further confirmed by Johansen and Juselius (JJ, 1992) test of cointegration on futures and spot prices of four currencies. The results indicate that all currencies exhibit the long-run relationship, confirming the prices discovery in spot and futures as well as the future prices from the two trading platforms for each currency.[10]

[Insert Table 6 about here]

Table 6 exhibits the Vector Error Correction Model (VECM) results. The ECT which is also called as speed of adjustment co-efficient βi, is exhibiting correct sign. The speed of adjustment in spot market for all four currencies is greater than the futures market, indicating that when the co-integrated series is in disequilibrium in the short-run, it is the spot price (cash market) that makes the greater adjustment than the futures price (futures market) in order to restore the equilibrium. In case of futures prices of both markets of all currencies with the exception of USDNSE, there are significant ECT terms, thereby implying that these

[10] Due to space constraint, we have avoided mentioning the results. However, the results of JJ tests are available with the authors upon request.

futures generally exhibit an equilibrium relationship and any departures from it are small and insignificant. To summarize, it can be said that in Indian currency market, it is the spot price that makes the greater adjustment in order to restore the equilibrium. In other words, futures price leads the spot price in price discovery in India's foreign exchange market. The price discovery results suggest that there is not only pricing efficiency between spot and futures prices but there is also efficient information transmission between the two futures exchanges.

5.2. Volatility spillovers

The study analyzes the volatility spillovers effects between spot and futures of four currencies and between two currency market platforms viz., MCX-SX and NSE. The estimated results are shown in Table 7-10 for sample currency. The BEKK model is used as the benchmark and its results are compared with two restricted correlation models (constant conditional correlation and dynamic conditional correlation). The BEKK model is the most computationally intensive of the models studied. Own conditional GARCH effects (β_{ii}), which measure long-term persistence, are clearly important in explaining conditional volatility (see Table 7-10). The estimated coefficients on the own conditional volatility effects, the β_{ii} terms, are statistically significant at the 1% level of significance and better, in each of the MGARCH models. The coefficient β_{11} refers to the GARCH term in the EUROMCX equation, while β_{22} refers to the GARCH term in the SEURO equation and β_{33} refers to the GARCH term in the EURONSE equation as shown in Table 7. For a particular market i, the estimated coefficients for β_{ii} are remarkably similar across the models. EUROMCX and EURONSE show the most amount of long-term persistence followed by SEURO. Own conditional ARCH effects (α_{ii}), which measure short-term persistence, are important in explaining the conditional volatility (Table 7). For each i, the estimated α_{ii}

values are smaller than their respective estimated β_{ii} values, indicating that own volatility long-run (GARCH) persistence is larger than short-run (ARCH) persistence.

[Insert Table 7 about here]

The results of BEKK model in case of Euro currency (EURO) also shown in Table 7 indicate several instances of significant volatility spillovers. In short term, MCX-SX indicates unidirectional volatility spillover between futures and spot i.e. ($\alpha_{1,\ 2}$), while, NSE exhibits bidirectional volatility spillovers between futures to spot ($\alpha_{1,\ 3}$). Both trading platforms exhibit stronger volatility spillovers from futures to spot, implying that the MCX-SX is suitable only for speculators while NSE favors both (hedgers and speculators). In long-term, MCX-SX indicates unilateral spillover effects ($\beta_{1,2}$), moving more strongly from spot to future. While, NSE exhibits the bilateral volatility spillovers ($\beta_{1,\ 3}$) moving strongly from futures to spot. The long-term results are notable in the sense that MCX-SX is lucrative destination for hedgers while NSE favors speculators. The results of volatility spillovers between futures of Euro currency on both trading platforms i.e. ($\alpha_{1,\ 3}$) and ($\alpha_{3,\ 1}$) indicate bilateral volatility spillovers in short as well as long-term. The results conclude that it is the MCX-SX which has stronger volatility spillover than EURONSE in short as well as long-run.

Similarly for USD, the BEKK results indicate that there are several instances of significant volatility spillovers (see Table 8). In short-term, both trading platforms exhibit bilateral volatility spillovers between futures and spot prices. The volatility spillovers are stronger from futures to spot prices in both markets (MCX-SX and NSE). In long-run, MCX-SX exhibits the bilateral volatility spillovers while NSE indicates unidirectional volatility spillover. In both trading platforms, the volatility spillovers move strongly from spot to futures. The results imply that both trading platforms are more suitable for hedgers than for speculators. However, the BEKK results of both markets (MCX-SX and NSE) of futures indicate that there are bilateral volatility spillovers between MCX-SX and NSE, with stronger volatility spillovers moving from MCX-SX to NSE in short-term. While, in the long-run there is unidirectional volatility spillovers moving strongly from NSE to MCX-SX. The volatility spillover effects of MCX-SX is stronger on NSE in short-term but it is the NSE which shows stronger volatility spillover effects on MCX-SX in the long-run. In other words, in the long-term NSE futures plays stronger role in volatility spillovers than MCX-SX.

The GARCH-BEKK results for GBP (British Pound) are shown in Table 9. The results indicate that there is unidirectional volatility spillover between futures and spot at both trading platforms, with stronger volatility moving from futures to spot in the short-run. While, in the long run both markets exhibit bidirectional volatility spillovers, with stronger spillovers moving from futures to spot than the spot to futures. The results indicate that both trading platforms are favourable for speculators in short as well as long-run. However, The BEKK results of both markets MCX-SX and NSE of futures indicate that there is no evidence of volatility spillover between two markets. However, in the long-run, there are bilateral volatility spillovers moving strongly from MCX-SX to NSE.

Lastly, the BEKK results of JPY (Japanese Yen) indicate that there are bidirectional volatility spillovers between futures and spot prices in short-term at MCX-SX and NSE (see Table 10). The volatility spillovers are stronger from futures to spot. In the long-term, both trading platforms indicate unidirectional volatility spillovers moving strongly from spot to futures, suggesting that the market is more favourable for both (hedgers as well as speculators). The BEKK results of both markets MCX-SX and NSE of futures indicate the evidence of no volatility spillovers in short-term but there are bilateral volatility spillovers moving strongly from MCX-SX to NSE.

The results of CCC model for sample currencies indicate highly positive correlations with significance level at 1% and better. In case of Euro (see Table 7), the highest correlation is between EURONSE and EUROMCX (ρ_{31}) followed by SEURO and EUROMCX (ρ_{21}). Similarly, for USD, the highest correlation is between USDNSE and USDMCX (ρ_{31}) i.e., 0.93 followed by SUSD and USDMCX (ρ_{21}) as 0.79 (see Table 8). In case of GBP, the highest correlation is between GBPNSE and GBPMCX (ρ_{31}) i.e., 0.98 followed by SGBP and GBPMCX (ρ_{21}) as 0.84 (see Table 9). For JPY, the highest correlation is also between JPYNSE and JPYMCX (ρ_{31}) i.e., 0.99 followed by SJPY and JPYMCX (ρ_{21}) as 0.91 (see Table 10). It may be noted that among all currencies, the highest correlation is found in case of JPY, implying that both trading platforms are highly synchronized in terms of trade facilitation and information transmission is stronger in futures of both markets. The BEKK, results are further substantiated by CCC model results in the sense that MCX-SX seems more informationally efficient trading platform than NSE.

The results of DCC model indicate that the estimated coefficients on θ_1 and θ_2 for examined currencies are positive and statistically significant at 1% level and better. These estimated coefficients sum to a value which is less than one, meaning that the dynamic conditional correlations of all currencies are mean reverting. Table 11 shows the diagnostic tests for the standardized residuals and its squared show no evidence of serial correlation at 5% level of significance and better. The results indicate no evidence of autocorrelation in the squared standardized residuals except JPY.

[Insert Table 11 about here]

6. Conclusion and discussion

This study investigates the price discovery and volatility spillovers between spot and futures prices of four currencies (viz., USD/INR, EURO/INR, GBP/INR and JPY/INR) traded on two stock exchanges i.e. NSE and MCX-SX in India. The sample period of the study starts from February 01, 2010 to February 29, 2012. The price discovery results confirm that there is a long-run equilibrium relationship between spot and futures prices as well as between the futures prices of two trading platforms even after accounting the structural break in each currency series, implying that there is informational efficiency in Indian foreign exchange market. The results of volatility spillovers under MGARCH framework indicate that short-term volatility spillovers are observed between futures and spot markets, which are stronger from futures to spot. Short-term volatility spillovers are also observed between the two futures markets which are stronger from MCX-SX to NSE. The findings imply that the information contained in the second moments of prices is incorporated faster in futures market than the spot market with MCX-SX appearing to be more efficient trading platform. In the long-run, bivariate volatility spillovers are generally observed which are stronger from spot to futures for all currencies with exception of Euro in case of NSE. The results are not surprising as the cash (OTC) market for these currencies is very well developed due to banks and corporate participation. In case of futures market linkages, there is a stronger volatility spillover from MCX-SX to NSE for all sample currencies with the exception of US dollar where the converse is true. Our findings suggest that futures derivative trading platforms are playing significant role in fair price discovery and volatility spillovers (both short as well as long-term). Hence, their operations are providing trading efficiency for currency market in India. MCX-SX seems to be more dominant platform for information transmission with the exception of US dollar while evaluating long-run relationship. From policy point of view, the currency derivatives market owing to its linkages with the underlying OTC market has contributed significantly to informational efficiency in the trading system. These futures market operations are helping in price discovery and providing information for price risk management. The recent volatility of rupee vis-a-vis major international currencies and its continuous weakening has raised some concern that speculative trading may have caused destabilization effects on spot prices. However, given that the currency distortions have continued for a long time (almost a year), it may require a more fundamental and constructive correction, the government needs to re-look at its inflation control policy by approaching the problem more from supply-side than the demand side. The focus should be on removing production bottlenecks, curb hoardings and balancing domestic demand with exports. Recent softening of oil prices may ease the government on the import front; it is high time that the government rolled down the interest rates which would encourage higher capital investment and stimulate growth. Further the interest rate correction shall ease the downward pressure on rupee vis-a-vis international currencies owing to interest rate parity linkages. The government should encourage wider institutional participation to increase market liquidity. However, till such time that full capital account convertibility is implemented, the FIIs should not be allowed into foreign exchange derivative market as their short-term actions will make the market more volatile and hence harm the interest of investors including hedgers. RBI should permit the currency exchanges for physical settlement of currencies through the designated banks' NOSTRO accounts. For this, the exchanges should be permitted to introduce intention of delivery. The hedgers should give the intention of delivery may be ten to fifteen days prior to settlement of contract. Once the delivery intention is received from the hedger, exchanges should remove the contracts from the open interest position. This will reduce the volatility and speculative pressure in currency derivative markets. Further to achieve higher transparency and better price discovery the OTC component of the market should be linked with the derivative segment.

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Table 1: Descriptive statistics for daily returns

	USDMCX	USDNSE	EUROMCX	EURONSE	GBPMCX	GBPNSE	JPYMCX	JPYNSE	SEURO	SGBP	SJAP	SUSD
Mean	0.005	0.006	0.002	0.002	0.006	0.006	0.016	0.016	0.002	0.005	0.015	0.005
Median	-0.002	0.005	0.002	-0.002	0.003	0.006	0.019	0.017	0.000	0.000	0.011	0.000
Max.	1.178	1.263	4.269	4.270	3.627	3.629	2.065	2.071	4.224	3.555	1.996	1.151
Min.	-2.175	-1.956	-4.073	-4.076	-1.281	-1.301	-3.248	-3.248	-4.205	-1.490	-3.331	-1.996
Std.Dev.	0.236	0.235	0.381	0.382	0.293	0.296	0.393	0.393	0.404	0.306	0.408	0.243
Skewness	-1.008	-0.621	0.387	0.378	3.680	3.558	-1.003	-1.012	0.069	2.832	-1.266	-0.717

Kurtosis	20.078	15.140	61.067	60.339	51.218	49.069	15.714	15.767	50.500	41.227	15.067	14.472
JB	5,927	2,984	67,589	65,903	47,682	43,551	3,320	3,349	45,219	29,930	3,047	2,679
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LB	21.617	19.994	33.621	33.105	17.959	16.853	12.489	12.819	34.504	22.851	19.362	22.177
	[0.361]	[0.458]	[0.028]*	[0.032]*	[0.590]	[0.662]	[0.898]	[0.884]	[0.022]*	[0.296]	[0.498]	[0.330]
LB^2	7.816	7.156	0.686	0.689	1.637	1.778	12.418	12.646	1.252	2.921	11.644	14.809
	[0.993]	[0.996]	[1.000]	[1.000]	[1.000]	[1.000]	[0.900]	[0.892]	[1.000]	[0.999]	[0.927]	[0.787]
Obs.	481	481	481	481	481	481	481	481	481	481	481	481

Note: * denotes the level of significance at 1% and better.

Table 2: Results of Zivot-Andrews Unit Root Test

Variables	t-statistics	Break period
SJAP	-3.3374	30-08-2010
JPYNSE	-3.2804	30-08-2010
JPYMCX	-3.2497	30-08-2010
SEURO	-4.5558	30-08-2010
EURONSE	-4.3661	30-08-2010
EUROMCX	-4.5403	30-08-2010
SUSD	-4.6471	24-05-2010
USDNSE	-4.6384	24-05-2010
USDMCX	-4.5716	24-05-2010
SGBP	-4.3465	25-05-2010
GBPNSE	-4.5293	25-05-2010
GBPMCX	-4.3514	25-05-2010
Critical values		
1%	-5.5700	
5%	-5.0800	

Note: all series exhibit non-stationarity, confirming the use of cointegration with regime shifts.

Table 3: Gregory and Hansen Cointegration Test (between spot and futures)

Variables	t-statistics	Period
SJAP on JPYNSE	-20.721**	15-09-2010
JPYNSE on SJAP	-20.709**	15-09-2010
JPYMCX on SJAP	-20.681**	15-09-2010
SJAP on JPYMCX	-20.694**	15-09-2010
SEURO on EURONSE	-18.896**	02-06-2010
EURONSE on SEURO	-18.853**	02-06-2010
EUROMCX on SEURO	-13.149**	30-08-2010
SEURO on EUROMCX	-13.236**	30-08-2010
GBPMCX on SGBP	-19.033**	26-05-2010
SGBP on GBPMCX	-19.066**	26-05-2010
GBPNSE on SGBP	-19.005**	26-05-2010
SGBP on GBPNSE	-19.005**	26-05-2010

USDNSE on SUSD	-13.235**	27-05-2010
SUSD on USDNSE	-13.227**	27-05-2010
USDMCX on SUSD	-8.104**	27-05-2010
SUSD on USDMCX	-8.078**	27-05-2010
Significance level critical values		
1%	-5.470	
5%	-4.950	

Note: ** indicates the level of significance at 1%. EG based GH test considers dependent and independent variable like linear regression.

Table 4. Gregory and Hansen Cointegration Test (between two markets)

Variables	t-statistics	Period
USDNSE on USDMCX	-5.783**	31-05-2010
USDMCX on USDNSE	-5.783**	31-05-2010
EUROMCX on EURONSE	-8.072**	10-08-2010
EURONSE on EUROMCX	-8.077**	10-08-2010
JPYMCX on JPYNSE	-6.483**	15-09-2010
JPYNSE on JPYMCX	-6.522**	15-09-2010
GBPMCX on GBPNSE	-7.309**	25-05-2010
GBPNSE on GBPMCX	-7.402**	25-05-2010
Significance level critical values		
1%	-5.470	
5%	-4.950	

Note: ** indicates the level of significance at 1%.

Table 5: Bai and Perron multiple structural break tests on sample currency series

	$SupF(l+1\|l)$ statistics to determine the number of breaks						
	supF (1|0)	*supF* (2|1)	*supF* (3|2)	*supF* (4|3)	Timing of breaks		
SJAP	4.43	36.47*	13.33**		30-08-2010	15-09-2010	
JPYNSE	4.38	39.44*	15.29**		30-08-2010	15-09-2010	
JPYMCX	4.35	39.16*	15.33**		30-08-2010	15-09-2010	
SEURO	5.23	65.27*	60.49*	32.61**	02-06-2010	30-08-2010	07-09-2010
EURONSE	5.29	79.35*	60.52*	43.25**	02-06-2010	30-08-2010	07-09-2010
EUROMCX	5.30	80.06*	61**	43.91**	02-06-2010	30-08-2010	07-09-2010
SGBP	15.2**	100.05*	12.73**		25-05-2010	21-06-2010	30-08-2010
GBPNSE	15.6**	94.94*	7.59		25-05-2010	30-08-2010	
GBPMCX	15.71**	98.04*	7.52		25-05-2010	30-08-2010	
SUSD	9.8**	34.61*			24-05-2010	26-05-2010	
USDNSE	10.49**	30.42*			24-05-2010	26-05-2010	
USDMCX	10.05**	45.72*			24-05-2010	26-05-2010	

Note: Based on LWZ criterion (see Perron, 1998 and 2002), the number of structural breaks is identified. The levels of significance of *supFT* (k) tests are shown for at ** 0.05, or * 0.1 level. The test has been conducted by using WINRATS procedure @baiperron to perform the tests.

Table 6: Estimated co-efficient of VEC model

Between spot and futures markets					
Currency Spot	co-efficient	t-stats	Currency futures	co-efficient	t-stats
$\beta_{2SJAP\ (mcx)}$	-0.8995	[-5.0356**]	$\beta_{1JPYMCX}$	0.0190	[0.1020]
$\beta_{2SUSD\ (mcx)}$	-0.3585	[0.9070]	$\beta_{1USDMCX}$	0.0911	[0.9070]
$\beta_{2SEURO\ (mcx)}$	-0.6084	[2.8418**]	$\beta_{1EUROMCX}$	-0.2511	[-1.1396]
$\beta_{2SGBP\ (mcx)}$	-0.5117	[-3.8666**]	$\beta_{1GBPMCX}$	-0.2591	[-1.8258**]
$\beta_{2SJAP\ (nse)}$	-0.8913	[-4.9848**]	$\beta_{1JPYNSE}$	0.0911	[0.9070]
$\beta_{2SUSD\ (nse)}$	-0.5761	[-4.1261**]	$\beta_{1USDNSE}$	-0.1402	[-0.8728]
$\beta_{2SEURO\ (nse)}$	-0.6816	[-3.2739**]	$\beta_{1EURONSE}$	-0.1267	[-0.5939]
$\beta_{2SGBP\ (nse)}$	-0.3839	[-2.1767**]	$\beta_{1GBPNSE}$	-0.3318	[-2.3604**]
Between futures markets of MCX-SX and NSE for all currencies					
$\beta_{2JPYMCX}$	-0.0220	[-0.0386]	$\beta_{1JPYNSE}$	-0.3700	[-0.6496]
$\beta_{2USDMCX}$	-0.1072	[-0.8300]	$\beta_{1USDNSE}$	-0.2530	[-1.9981**]
$\beta_{2EUROMCX}$	-0.3146	[-0.2806]	$\beta_{1EURNSE}$	-0.0566	[-0.0504]
$\beta_{2GBPMCX}$	-0.1596	[-0.4776]	$\beta_{1GBPNSE}$	-0.0269	[-0.0801]

Note: (1) ** denotes the level of significance of *t-statistics* as shown in parentheses at 5% and better.
(2). Appropriate lag has been selected for each series under VAR framework.
(3). $\beta_{2SJAP\ (mcx)}$ indicates spot series of Japanese Yen as dependent variable with future price series of MCX (JPYMCX). Other commodities will also be interpreted in similar manner.

Table 7: MGARCH Results: EURO/INR

	BEKK			**CCC**			**DCC**		
Variable	**Coeff**	**t-stat**	**Signif**	**Coeff**	**t-stat**	**Signif**	**Coeff**	**t-stat**	**Signif**
μ_1	0.023	16.392	0.000	-0.016	-0.391	0.696	-0.088	-26.040	0.000
μ_2	-0.031	-2.491	0.013	-0.015	-0.374	0.709	-0.091	-7.040	0.000
μ_3	0.015	9.995	0.000	-0.016	-0.396	0.692	-0.090	-26.334	0.000
$c_{(1,1)}$	0.682	13.540	0.000	1.832	3.175	0.001	0.149	102.676	0.000
$c_{(2,1)}$	0.896	13.032	0.000						
$c_{(2,2)}$	-0.067	-0.213	0.832	0.071	1.801	0.072	0.191	67.687	0.000
$c_{(3,1)}$	0.680	13.302	0.000						
$c_{(3,2)}$	0.000	-0.084	0.933						
$c_{(3,3)}$	0.000	0.000	1.000	1.822	3.189	0.001	0.148	167.792	0.000
$\alpha_{(1,1)}$	-0.414	-27.571	0.000	-0.007	-3.062	0.002	0.109	56.041	0.000
$\alpha_{(1,2)}$	-0.432	-2.483	0.013						
$\alpha_{(1,3)}$	-1.050	-102.176	0.000						
$\alpha_{(2,1)}$	0.002	0.074	0.941						
$\alpha_{(2,2)}$	-0.028	-0.246	0.806	-0.004	-2.283	0.022	0.097	15.017	0.000
$\alpha_{(2,3)}$	0.059	2.197	0.028						
$\alpha_{(3,1)}$	0.429	41.576	0.000						
$\alpha_{(3,2)}$	0.439	2.060	0.039						
$\alpha_{(3,3)}$	1.012	63.786	0.000	-0.008	-3.120	0.002	0.108	79.311	0.000
$\beta_{(1,1)}$	0.631	40.894	0.000	-0.798	-9.644	0.000	0.744	465.284	0.000
$\beta_{(1,2)}$	-0.049	-0.157	0.876						
$\beta_{(1,3)}$	-0.118	-9.853	0.000						
$\beta_{(2,1)}$	0.057	3.685	0.000						
$\beta_{(2,2)}$	0.201	0.551	0.581	0.934	27.626	0.000	0.704	209.086	0.000
$\beta_{(2,3)}$	0.056	3.303	0.001						
$\beta_{(3,1)}$	0.047	3.127	0.002						

$\beta_{(3,2)}$	0.291	2.099	0.036						
$\beta_{(3,3)}$	0.795	48.512	0.000	-0.787	-9.092	0.000	0.746	727.753	0.000
$\rho_{(2,1)}$				0.930	39.831	0.000			
$\rho_{(3,1)}$				0.997	697.355	0.000			
$\rho_{(3,2)}$				0.929	39.135	0.000			
$\theta_{(1)}$							0.124	39.220	0.000
$\theta_{(2)}$							0.787	155.923	0.000

Note: Models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. Variable order is EUROMCX (1), SEURO (2) and EURONSE (3). In the variance equations, c denotes the constant terms, α denotes the ARCH terms and β denotes the GARCH terms.. The coefficient α13 for example represents the short-term volatility spillover from EUROMCX to EURONSE while β13 represents the long-term volatility spillover from EUROMCX to EURONSE. There are 481 observations.

Table 8: MGARCH Results: USD/INR

	BEKK			**CCC**			**DCC**		
Variable	**Coeff**	**t-stat**	**Signif**	**Coeff**	**t-stat**	**Signif**	**Coeff**	**t-stat**	**Signif**
μ_1	-0.015	-0.448	0.654	-0.036	-1.036	0.300	-0.058	-6.456	0.000
μ_2	0.020	0.523	0.601	-0.033	-1.089	0.276	-0.057	-2.775	0.006
μ_3	0.019	0.503	0.615	-0.036	-0.990	0.322	-0.034	-3.533	0.000
$c_{(1,1)}$	0.573	16.233	0.000	0.162	1.930	0.054	0.156	20.908	0.000
$c_{(2,1)}$	0.693	15.814	0.000						
$c_{(2,2)}$	0.025	0.309	0.758	0.222	2.373	0.018	0.170	11.945	0.000
$c_{(3,1)}$	0.626	16.891	0.000						
$c_{(3,2)}$	0.098	0.682	0.495						
$c_{(3,3)}$	0.002	0.005	0.996	0.143	0.698	0.485	0.208	33.287	0.000
$\alpha_{(1,1)}$	-1.868	-14.974	0.000	0.081	3.034	0.002	0.205	30.773	0.000
$\alpha_{(1,2)}$	-1.850	-24.940	0.000						
$\alpha_{(1,3)}$	-1.253	-6.460	0.000						
$\alpha_{(2,1)}$	0.500	3.853	0.000						
$\alpha_{(2,2)}$	0.330	1.758	0.079	0.261	3.753	0.000	0.359	16.653	0.000
$\alpha_{(2,3)}$	0.394	3.150	0.002						
$\alpha_{(3,1)}$	0.899	8.931	0.000						
$\alpha_{(3,2)}$	0.970	6.941	0.000						
$\alpha_{(3,3)}$	0.380	1.857	0.063	0.040	0.902	0.367	0.176	25.548	0.000
$\beta_{(1,1)}$	0.336	11.635	0.000	0.746	7.295	0.000	0.667	96.246	0.000
$\beta_{(1,2)}$	-0.374	-5.595	0.000						
$\beta_{(1,3)}$	-0.002	-0.045	0.964						
$\beta_{(2,1)}$	-0.407	-4.345	0.000						
$\beta_{(2,2)}$	0.146	0.973	0.330	0.515	3.645	0.000	0.543	35.220	0.000
$\beta_{(2,3)}$	-0.742	-4.703	0.000						
$\beta_{(3,1)}$	0.427	4.370	0.000						
$\beta_{(3,2)}$	0.202	1.233	0.218						
$\beta_{(3,3)}$	0.876	7.798	0.000	0.819	3.432	0.001	0.660	122.903	0.000
$\rho_{(2,1)}$				0.793	32.764	0.000			
$\rho_{(3,1)}$				0.936	84.046	0.000			
$\rho_{(3,2)}$				0.775	28.807	0.000			
$\theta_{(1)}$							0.179	10.951	0.000

$\theta_{(2)}$							0.491	12.923	0.000

Note: Models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. Variable order is MCX-SX (1), SPOT (2) and NSE (3). In the variance equations, c denotes the constant terms, α denotes the ARCH terms and β denotes the GARCH terms. The coefficient α13 for example represents the short-term volatility spillover from MCX-SX to NSE while β13 represents the long-term volatility spillover from MCX-SX to NSE. There are 467 observations.

Table 9: MGARCH Results: GBP/INR

	BEKK			CCC			DCC		
Variable	**Coeff**	**t-stat**	**Signif**	**Coeff**	**t-stat**	**Signif**	**Coeff**	**t-stat**	**Signif**
μ_1	-0.068	-1.293	0.196	-0.059	-1.375	0.169	0.015	4.377	0.000
μ_2	-0.086	-1.879	0.060	-0.058	-1.415	0.157	0.012	0.618	0.537
μ_3	-0.073	-1.404	0.160	-0.059	-1.363	0.173	0.009	2.674	0.007
$c_{(1,1)}$	0.409	5.670	0.000	0.007	12.480	0.000	0.007	14.800	0.000
$c_{(2,1)}$	0.101	1.743	0.081						
$c_{(2,2)}$	0.001	0.009	0.993	0.355	1.058	0.290	0.005	4.000	0.000
$c_{(3,1)}$	0.401	5.201	0.000						
$c_{(3,2)}$	0.000	0.016	0.987						
$c_{(3,3)}$	0.000	0.008	0.994	0.170	22.982	0.000	0.007	13.052	0.000
$\alpha_{(1,1)}$	0.669	2.547	0.011	0.000	-0.726	0.468	0.063	94.945	0.000
$\alpha_{(1,2)}$	0.610	2.653	0.008						
$\alpha_{(1,3)}$	0.342	1.157	0.247						
$\alpha_{(2,1)}$	-0.017	-0.100	0.920						
$\alpha_{(2,2)}$	0.333	2.308	0.021	0.181	1.186	0.236	0.050	33.303	0.000
$\alpha_{(2,3)}$	-0.054	-0.319	0.750						
$\alpha_{(3,1)}$	-0.459	-1.589	0.112						
$\alpha_{(3,2)}$	-0.574	-2.644	0.008						
$\alpha_{(3,3)}$	-0.089	-0.251	0.802	0.001	0.650	0.516	0.065	87.793	0.000
$\beta_{(1,1)}$	-0.471	-2.073	0.038	0.992	2047.729	0.000	0.940	1834.550	0.000
$\beta_{(1,2)}$	-1.571	-4.531	0.000						
$\beta_{(1,3)}$	-1.348	-5.739	0.000						
$\beta_{(2,1)}$	0.873	6.230	0.000						
$\beta_{(2,2)}$	1.477	14.519	0.000	0.479	1.152	0.249	0.951	882.253	0.000
$\beta_{(2,3)}$	0.843	5.998	0.000						
$\beta_{(3,1)}$	0.490	1.996	0.046						
$\beta_{(3,2)}$	0.828	2.859	0.004						
$\beta_{(3,3)}$	1.398	5.030	0.000	0.822	102.270	0.000	0.939	1667.368	0.000
$\rho_{(2,1)}$				0.849	43.603	0.000			
$\rho_{(3,1)}$				0.989	309.266	0.000			
$\rho_{(3,2)}$				0.841	44.276	0.000			
$\theta_{(1)}$							0.055	42.151	0.000
$\theta_{(2)}$							0.942	599.344	0.000

Note: Models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. Variable order is MCX-SX (1), SPOT (2) and NSE (3). In the variance equations, c denotes the constant terms, α denotes the ARCH terms and β denotes the GARCH terms.. The coefficient α13 for example represents the short-term volatility spillover from MCX-SX to NSE while β13 represents the long-term volatility spillover from MCX-SX to NSE. There are 467 observations.

Table 10: MGARCH Results: JPY/INR

	BEKK			CCC			DCC		
Variable	**Coeff**	**t-stat**	**Signif**	**Coeff**	**t-stat**	**Signif**	**Coeff**	**t-stat**	**Signif**
μ_1	-0.094	-4.782	0.000	0.010	0.239	0.811	0.032	20.407	0.000
μ_2	-0.100	-5.351	0.000	0.005	0.127	0.899	0.005	0.493	0.622
μ_3	-0.096	-4.860	0.000	0.010	0.232	0.817	0.032	21.447	0.000
$c_{(1,1)}$	0.809	20.236	0.000	0.287	12.172	0.000	0.217	260.858	0.000
$c_{(2,1)}$	0.599	12.461	0.000						
$c_{(2,2)}$	0.344	14.300	0.000	0.371	9.868	0.000	0.969	107.363	0.000
$c_{(3,1)}$	0.806	20.145	0.000						
$c_{(3,2)}$	0.001	0.403	0.687						
$c_{(3,3)}$	0.000	-0.001	0.999	0.331	14.812	0.000			
$\alpha_{(1,1)}$	0.991	64.397	0.000	-0.013	-4.096	0.000	0.210	291.696	0.000
$\alpha_{(1,2)}$	1.918	5.101	0.000				0.148	188.602	0.000
$\alpha_{(1,3)}$	0.310	14.131	0.000						
$\alpha_{(2,1)}$	-0.582	-11.724	0.000						
$\alpha_{(2,2)}$	-0.680	-6.111	0.000	0.000	0.019	0.985	0.293	15.656	0.000
$\alpha_{(2,3)}$	-0.571	-11.597	0.000						
$\alpha_{(3,1)}$	-1.179	-65.551	0.000						
$\alpha_{(3,2)}$	-2.176	-5.941	0.000						
$\alpha_{(3,3)}$	-0.514	-41.590	0.000	-0.013	-3.759	0.000	0.145	208.671	0.000
$\beta_{(1,1)}$	0.557	42.255	0.000	0.732	18.757	0.000	0.692	1436.741	0.000
$\beta_{(1,2)}$	0.203	0.829	0.407						
$\beta_{(1,3)}$	-0.310	-23.866	0.000						
$\beta_{(2,1)}$	-0.299	-11.070	0.000						
$\beta_{(2,2)}$	-0.396	-3.029	0.002	0.631	12.890	0.000	-0.010	-1.210	0.226
$\beta_{(2,3)}$	-0.298	-11.521	0.000						
$\beta_{(3,1)}$	-0.176	-15.717	0.000						
$\beta_{(3,2)}$	0.293	1.460	0.144						
$\beta_{(3,3)}$	0.693	59.206	0.000	0.689	15.245	0.000	0.700	1706.060	0.000
$\rho_{(2,1)}$				0.910	47.695	0.000			
$\rho_{(3,1)}$				0.995	429.168	0.000			
$\rho_{(3,2)}$				0.907	46.454	0.000			
$\theta_{(1)}$							0.089	291.876	0.000
$\theta_{(2)}$							0.908	2815.361	0.000

Note: Models estimated using QMLE with robust (heteroskedasticity/misspecification) standard errors. Variable order is MCX-SX (1), SPOT (2) and NSE (3). In the variance equations, c denotes the constant terms, α denotes the ARCH terms and β denotes the GARCH terms.. The coefficient α13 for example represents the short-term volatility spillover from MCX-SX to NSE while β13 represents the long-term volatility spillover from MCX-SX to NSE. There are 467 observations.

Table 11: Diagnostic tests for standardized residuals

BEKK	**USD**	**P-values**	**EURO**	**P-values**	**GBP**	**P-values**	**JPY**	**P-values**
Q (20)	21.675	0.358	19.554	0.486	16.578	0.680	14.656	0.795
Q sqr(20)	26.556	0.148	19.447	0.493	21.065	0.393	32.306**	0.040
CCC	**USD**	**P-values**	**EURO**	**P-values**	**GBP**	**P-values**	**JPY**	**P-values**
Q (20)	18.962	0.524	19.671	0.479	15.671	0.737	14.011	0.830

Q sqr(20)	19.788	0.471	21.672	0.359	23.282	0.275	23.878	0.248
DCC	**USD**	**P-values**	**EURO**	**P-values**	**GBP**	**P-values**	**JPY**	**P-values**
Q (20)	18.778	0.536	20.036	0.456	12.057	0.914	11.409	0.935
Q sqr(20)	19.530	0.488	22.188	0.330	17.225	0.638	28.112	0.107

Note: ** shows the level of significance at 5% and better.