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Contagion in Futures FOREX Markets for the Post-Global Financial Crisis: A Multivariate FIGARCH-cDCC Approach

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Abstract

This paper seeks to investigate the time-varying conditional correlations to the futures FOREX market returns. We employ a dynamic conditional correlation (DCC) Generalized ARCH (GARCH) model to find potential contagion effects among the markets. The under investigation period is 2014-2019. We focus on four major futures FOREX markets namely JPY/USD, KRW/USD, EUR/USD and INR/USD. The empirical results show an increase in conditional correlation or contagion for all the pairs of future FOREX markets. Based on the dynamic conditional correlations, KRW/USD seems to be the safest futures FOREX market. The results are of interest to policymakers who provide regulations for the futures FOREX markets.

Keywords: Financial contagion, Global Financial Crisis, cDCC-FIGARCH model, future FOREX market

JEL Classification Codes: C58, C61, G11, G15

1. Introduction

The purpose of this paper is to investigate the potential contagion effects among four major futures FOREX markets by taking into account the volatility transmission between the markets. We consider the JPY/USD, KRW/USD, EUR/USD and INR/USD futures FOREX markets from 2014 to 2019. We quantify contagion using the dynamic conditional correlation (DCC) Generalized ARCH (GARCH) model.

The motivation for examining contagion is as follows. First, to the best of our knowledge, there is no other empirical research investigating the conditional second moments of the distribution of among futures FOREX markets (Figure 1) (spillover effects) (Allen & Gale, 2000; Caramazza, Rizzi & Salgado, 2004; Kaminsky, Carmen & Vegh, 2002). Spillovers refer to the impact that events in one market can have on another market. Second, the existence of contagion between the above markets is of great importance, since the under investigation period is the aftermath of the global financial crisis of 2008. Fourth, contagion results reveal common explanatory factors, revealing an underlying financial mechanism.

Furthermore, three interesting aspects emerged from this paper. Firstly, based on the descriptive statistics, JPY/USD demonstrates the largest fluctuations compared to the rest markets, indicating that JPY/USD is the most immune futures FOREX market. Secondly, the results of the cDCC- FIGARCH(1,d,1) model show the existence of volatility spillovers. Thirdly, dynamic conditional correlations show evidence of contagion for all the pairs of markets.

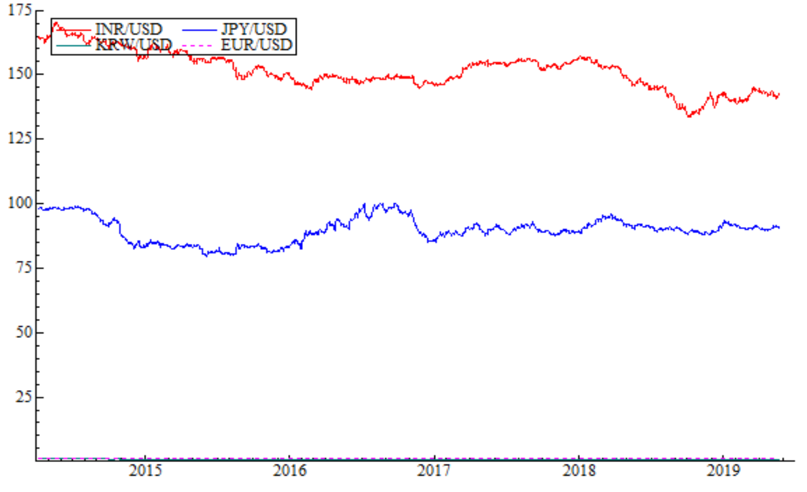

Figure 1: Actual Series Of Future Markets

Notes: Data from Datastream. The lines represent the future markets for JPY/USD, KRW/USD, EUR/USD and INR/USD.

2. Literature Review

The main body of the current literature investigates the linkages between derivative markets with financial markets (Belke & Gokus 2011; Fonseca & Gottschalk; 2012; Tokat 2013). Belke and Gokus (2011) examine the volatility transmission among the daily equity prices, CDS premiums and bond yields returns for four large US banks for the period 2006–2009. By employing a BEKK-GARCH model, they capture spillover effects. Fonseca and Gottschalk (2012) examine the volatility spillovers among CDS premium and equity returns for Australia, Japan, Korea and Hong Kong at firm and index level. They use weekly data during the period 2007–2010 and they show empirical evidence of spillover effects. Tokat (2013) empirically3 investigates the spillover effects between daily 5-year maturity sovereign CDS values for Brazil and Turkey denominated in USD, iTraxx XO index and CDX index during the period from 2005 to 2011. He employs a full BEKK-GARCH model and he proves empirically the existence of spillovers.

Additionally, there are several studies investigating linkages between oil crude oil future contracts with macroeconomic figures, financial markets and commodities. (Haigh & Holt, 2002; Guo & Kliesen, 2005; Malik & Hammoudeh, 2007; Driesprong, Jacobsen, & Maat, 2008). Haigh & Holt (2002) develop a theoretical model for a representative energy trader that simultaneously employs crude oil, heating oil, and natural gas futures to hedge future price uncertainty. They use weekly spot and future price data during the period from 7th December 1984 until 26th September 1997 for crude oil, unleaded gasoline and 2 heating oil sourced from Bridge/CRB. They find that the multivariate GARCH methodology, which takes into account volatility spillovers between markets, reduces significantly the uncertainty. Guo and Kliesen (2005) examine whether crude oil futures prices have a negative and significant effect on future gross domestic product (GDP) growth. They use daily values of crude oil futures traded on the New York Mercantile Exchange (NYMEX) during the period 1984–2004 by employing granger causality tests. The results confirm their hypothesis of a negative effect from crude oil futures prices to future gross domestic returns when incorporating oil price changes in their model.

We use the raw definition of contagion, suggested by Forbes and Rigobon (2002): contagion is defined as a significant increase in cross market linkages after a shock. Although the literature around the financial contagion in futures commodity markets is still limited, there are empirical studies investigating the contagion effects among different future commodity markets (Serra, 2011; Singh, Kumar & Pandey, 2010; Killian, 2008), although the most investigated futures markets are those of crude oil (Mensi, Beljid, Boubaker & Managi, 2013; Bekiros & Diks, 2008; Huang, Yang & Hwang, 2009; Maslyuk & Smyth, 2009) and gold (Baur & Lucey, 2010; Baur & McDermott, 2010; Smales, 2015).

Within the framework of volatility spillovers (Schnabel & Shin, 2004; Van Rijckeghem & Weder, 2001; Forbes, 2001; Clark, 1973), the investigation of commodity futures markets is of great importance, since an investment into this market can be generated by any investor or any speculator (Belousova & Dorfleitner, 2012; Silvennoinen & Thorp, 2013; Karyotis & Alijani, 2016). From an investor's perspective, commodity futures are a popular investment for a portfolio (Cartwright & Riabko, 2015; Aboura & Chevallier, 2015; Huchet & Gueye Fam, 2016). Dynamic conditional correlations between commodity futures are now at the center of financial literature (Wu & Zhang, 2005; Tao & Green, 2012; Rittler 2012; Chou & Chung, 2006). This study provides new empirical evidence on information transmission in futures FOREX markets.

3. The Model

We use the univariate FIGARCH(p,d,q) model to quantify the standardized residuals (first subsection). Then, we use the estimated standardized residuals to produce the multivariate conditional variance matrix by employing a cDCC model (second subsection). Last subsection presents the log-likelihood theoretical framework.

3.1. Univariate FIGARCH(p,d,q) Model

By using a constant (μ), the empirical set-up of the mean equation for the daily future market returns (y_t) is represented by the following equation:

$$y_t = \mu + \varepsilon_t, \text{ with } t = 1,\ldots,T. \tag{1}$$

ε_t is the standardized residuals such that:

$$\varepsilon_t = \sqrt{h_t}u_t, \text{ where } \varepsilon_t \sim N(0, H_t) \text{ and } u_t \sim N(0,1) \tag{2}$$

where h_t is defined as the univariate conditional variance matrix and u_t is the standardized errors. Furthermore, H_t is the multivariate conditional variance matrix.

It follows the definition of the univariate FIGARCH(*p*,*d*,*q*) model (Baillie, Bollerslev & Mikkelsen, 1996) to generate the conditional variance matrix (h_t):

$$h_t = \omega[1 - b(L)]^{-1} + \{1 - [1 - b(L)]^{-1}\Phi(L)(1 - L)^d\}\varepsilon_t^2 \tag{3}$$

where ω is mean of the logarithmic conditional variance, $\Phi(L) = [1 - a(L) - b(L)](1 - L)^{-1}$ is lag polynomial of order p and $(1 - L)^d$ is fractional difference operator. Additionally, *b(L)* and *a(L)* are autoregressive polynomials of order p and q so that: $b(L) = 1 - \sum_{k=1}^{p} b_k L^k$ and $a(L) = 1 + \sum_{l=1}^{q} a_l L^l$.

Furthermore, the selected lag order is equal to 1, as many other researchers have mentioned as sufficient to estimate the univariate conditional variance matrix, i.e. Bolleslev, Chou and Kroner, (1992), among others.

3.2 Multivariate cDCC Model

To model the dynamics of the conditional variance of the standardized residuals (ε_t), we employ the cDCC model of Aielli (2009). In this model, the variance covariance matrix(H_t) (*N x N* matrix) evolves according to:

$$H_t = D_t R_t D_t \tag{4}$$

where $D_t = diag\left(h_{11t}^{\frac{1}{2}} \dots h_{NNt}^{\frac{1}{2}}\right)$, *N* is the number of markets (i = 1,…,*N*). In this model the correlation matrix (R_t) is given by the transformation:

$$R_t = diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}})Q_t diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) \tag{5}$$

In addition, we define $P_t = diag\left(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}\right)$ and $u_t^* = P_t u_t$.

where $Q_t = (q_{ij,t})$ (N x N symmetric positive definite matrix) in turn follows:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}^{*} u_{t-1}^{*\prime} + \beta Q_{t-1} \tag{6}$$

where $\bar{Q}$ is the N x N unconditional variance matrix of u_t^* (since $\mathrm{E}[u_t^* u_t^{*\prime} \mid \Omega_{t-1}] = Q_t$)[1]. α and β are nonnegative scalar parameters ($\alpha + \beta < 1$).

For the cDCC model, the estimation of the matrix $\bar{Q}$ and the parameters α and β are intertwined, since $\bar{Q}$ is estimated sequentially by the correlation matrix of the u_t^*. To obtain u_t^* we need however a first step estimator of the diagonal elements of Q_t. Thanks to the fact that the diagonal elements of Q_t do not depend on $\bar{Q}$ (because $\overline{Q_{ii}} = 1$ for i = 1,…,N), Aielli (2009) proposed to obtain these values $q_{11,t}$,.., $q_{NN,t}$ as follows:

$$q_{ii,t} = (1 - \alpha - \beta) + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1} \tag{7}$$

for i = 1,…,N. In short, given α and β, we can compute $q_{11,t}$,.., $q_{NN,t}$ and thus u_t^*, then we can estimate $\bar{Q}$ as the empirical covariance of u_t^*.

3.3 Log-likelihood Estimation

In order to estimate the model, we use Full Information Maximum Likelihood (FIML) methods with student's t-distributed errors:

$$\sum_{t=1}^{T}\left[log\,\frac{\Gamma\left(\frac{\nu+k}{2}\right)}{[\nu\pi]^{\frac{k}{2}}\Gamma\left(\frac{\nu}{2}\right)\nu-2^{\frac{k}{2}}} - \frac{1}{2}\log\left(|H_t|\right) - \left(\frac{k+\nu}{2}\right) log\left[1 + \frac{\varepsilon_t{}' H_t{}^{-1}\varepsilon_t}{\nu-2}\right]\right] \tag{8}$$

where $\Gamma(.)$ is the Gamma function, k is the number of equations, and ν is the degrees of freedom.

4. Data Characteristics

We base my analysis on daily data for four future FOREX markets, namely JPY/USD, KRW/USD, EUR/USD and INR/USD. We obtained data from *Datastream® Database*. JPY/USD, KRW/USD

[1]Aielli (2009) has recently shown that the estimation of $\bar{Q}$ as the empirical correlation matrix of u_t is inconsistent because: $\mathrm{E}[u_t u_t]$= $\mathrm{E}[\mathrm{E}[u_t' u_t \mid \Omega_{t-1}] = \mathrm{E}[R_t] \neq \mathrm{E}[Q_t]$.

and INR/USD are traded on DGCX (Dubai Gold and Commodities Exchange) and EUR/USD is traded on EUREX[2]. The sample period entails the after crisis period: from 9th April 2014 until 21st May 2019. We use 1336 observations for each market. Future market returns are generated by $r_t = log(p_t) - log(p_{t-1})$, where p_t is the price of future market on day *t* and p_{t-1} is the price of future market on day *t*-1.

Appendix A shows the summary statistics for future FOREX market returns. JPY/USD shows larger fluctuations compared to the rest markets, considering the highest maximum (0,015012) the lowest minimum return (-0,011822) values and the std. deviation (0,0023655). In addition, all future FOREX market returns are positively skewed, except the case of INR/USD. Moreover, all market returns present excess kurtosis (fat tails). Jarque-Bera statistic results suggest the rejection of the null hypothesis of normality for all markets. ADF unit-root test results imply that the market returns are appropriate for further testing. The ARCH tests imply the presence of heteroskedasticity for all markets. The GPH test results show that JPY/USD future market has long memory ($0 < d < 0,5$) and the rest future markets (KRW/USD, EUR/USD, INR/USD) are anti-persistent processes ($-0,5 < d < 0$).

In Appendix B, the actual series of future markets and their respective logarithmic returns are graphed for INR/USD (Graph A), JPY/USD (Graph B), KRW/USD (Graph C) and EUR/USD (Graph D). The most striking characteristics of the graphs are: (1) all actual series follow a downward trend, and (2) all market returns are highly volatile.

5. Empirical Results

We divide this section into three subsections. In the first subsection, we show the empirical results from the cDCC-AR(1)-FIGARCH(1,d,1) model. In the second subsection, we present the estimates of Spearman's rank correlation. Third subsection demonstrates the mean values of conditional variances and covariances. Fourth subsection states the dynamic conditional correlation coefficients.

[2]The Eurex is the world's largest futures and options market. It offers global access to mostly Europe-based derivatives.

Table 1: Estimates of Univariate FIGARCH(1,d,1) Model, Sample Period: 9th April, 2014 – 21st May, 2019

	JPY/USD	KRW/USD	EUR/USD	INR/USD
constant (μ)	-0,0000964	-0,0000125	-0,0001014**	0,0000113
t-Statistic	-1,956	-0,2362	-2,164	0,3027
p-Value	0,0507	0,8133	0,0307	0,7622
constant (ω)	0,141788	0,025483	0,016777	1,263022***
t-Statistic	1,180	1,697	1,468	4,262
p-Value	0,2384	0,0900	0,1424	0,0000
d-Figarch	0,393050***	1,054844***	0,890055***	0,187616***
t-Statistic	3,719	11,30	9,480	5,408
p-Value	0,0002	0,0000	0,0000	0,0000
ARCH (a)	0,304354***	-0,047384	0,092237	-0,650094***
t-Statistic	2,648	-0,5734	1,194	-4,619
p-Value	0,0082	0,5665	0,2325	0,0000
GARCH (b)	0,644615***	0,960414***	0,938285***	-0,535188***
t-Statistic	4,106	47,59	41,07	-3,387
p-Value	0,0000	0,0000	0,0000	0,0007

Notes. Table 1 presents the results of univariate AR(1)-FIGARCH(1,d,1) model. ** and *** signify statistical significance at the 5% and 1% levels, respectively.

5.1. Empirical results of the cDCC- FIGARCH(1,d,1) model

Table 1 above shows that in the mean equation (Equation 1) only EUR/USD exhibit significant constant (μ). Regarding FIGARCH results (Equation 3), we notice significant constant (ω) only for INR/USD. While all markets demonstrate strong persistent behaviour (0<d-Figarch<1), KRW/USD has roughly long memory (d-Figarch really close to 1). We notice significant ARCH effects (α) only JPY/USD and INR/USD. All markets demonstrate significant GARCH effects (b).Table 2 below presents the results of cDCC model (Equation 6 and Equation 8). We observe significant ARCH (α) and GARCH effects (β). In addition, the degrees of freedom and the log-likelihood are stated. $x^2(8)$ statistic results suggest the rejection of the null hypothesis of no spillovers at 1% significance level. Ljuing-Box test results (Hosking 1980, Li-McLeod 1983) shoe evidence of no serial autocorrelation, indicating the absence of misspecification errors. Additionally, we provide the AIC and SIC information criteria for the selected model.

Table 2: Estimates of Fourvariate cDCC Model, Degrees of Freedom, Log-likelihood, Diagnostic Tests and Information Criteria, Sample period: 9th April, 2014 – 21st May, 2019

Panel A: estimates of cDCC model	**JPY/USD-KRW/USD-EUR/USD-INR/USD**
alpha *(α)*	0,011784***
t-Statistic	2,624
p-Value	0,0088
beta *(β)*	0,972903***
t-Statistic	68,35
p-Value	0,0000
degrees of freedom *(ν)*	6,878966***
t-Statistic	10,97
p-Value	0,0000
log-likelihood	25972,674
Panel B: diagnostic tests	
x^2(8)	466,21**
p-Value	0,0000
Hosking^2 (20)	357,755
p-Value	0,0616261
Li-McLeod^2 (20)	357,780
p-Value	0,0615129
Panel C: Information Criteria	
Akaike	0,014288
Schwarz	0,237243

Notes: Panel A shows the results of the conditional correlation driving process Q_t, the degrees of freedom and the log-likelihood. Panel B demonstrates the diagnostic tests of Hosking (1980) and McLeod and Li (1983). In Panel C we see the information criteria of AR(1)-FIGARCH(1,d,1)-cDCC model. The symmetric positive definite matrix Q_t is generated using one lag of Q and of u^*. P-values have been corrected by 2 degrees of freedom for Hosking^2 (50) and Li-McLeod^2 (50) statistics. ** and *** signify statistical significance at the 5% and 1% levels, respectively.

5.2. Simple Correlation Analysis

We use Sprearman's rank correlation to measure the financial contagion phenomenon by computing the mean correlations. Given the T observations, the T raw scores i_t, j_t ($i \neq j = 1,\ldots,N$ markets and $t = 1,\ldots,T$ observations) are converted to ranks rg_i, rg_j.

Table 3: Estimates of Spearman's Rank Correlation Coefficient(ρ_{rg_i,rg_j}), Sample Period: 9th April, 2014 –21st May, 2019

Market i	JPY/USD (i=1)	KRW/USD (i=2)	EUR/USD (i=3)	INR/USD (i=4)
ρ_{rg_i,rg_1}	**1**			
t-Statistic	-			
p-Value	-			
ρ_{rg_i,rg_2}	0,053624	**1**		
t-Statistic	1,088	-		
p-Value	0,2770	-		
ρ_{rg_i,rg_3}	0,309190***	0,257559***	**1**	
t-Statistic	6,770	5,452	-	
p-Value	0,0000	0,0000	-	
ρ_{rg_i,rg_4}	0,099558**	0,341865***	0,210200***	**1**
t-Statistic	2,031	8,380	2,624	-
p-Value	0,0425	0,0000	0,0088	-

Notes: Table 3 exhibits the estimates of elements (ρ_{rg_i,rg_j}) of rank correlation. ** and *** signify statistical significance at the 5% and 1% levels, respectively.

Using the covariance of the rank variables ($cov(rg_i, rg_j)$) and the standard deviations of the rank variables (σ_{rg_i} and σ_{rg_j}), we calculate the correlation coefficients (ρ_{rg_i,rg_j}) as follows:

$$\rho_{rg_i,rg_j} = \frac{cov(rg_i,rg_j)}{\sigma_{rg_i}\sigma_{rg_j}} \tag{9}$$

We show the empirical results above in table 3. Results reveal the highest rank correlation for the pairs of markets KRW/USD-INR/USD (ρ_{rg_2,rg_4}), JPY/USD-EUR/USD (ρ_{rg_1,rg_3}) and KRW/USD-EUR/USD (ρ_{rg_2,rg_3}). In addition, we observe that the Spearman's rank correlation between JPY/USD and KRW/USD(ρ_{rg_1,rg_2}) is not statistically significant, indicating a lower level of integration between the two markets.

5.3. Mean Values of Conditional Variances and Covariances

Appendix C states the estimated mean values ($\overline{h_{ij}}$, with $i, j = 1, \ldots, N$) of conditional variances and covariances. Weassume that the mean values reflect the own volatility and the cross-volatility spillover effects. We generate and store the conditional variances and covariances by employing the cDCC -FIGARCH model and then, we estimate the mean values.

The mean values of conditional variances reveal that $\overline{h_{2,2}} > \overline{h_{1,1}} > \overline{h_{3,3}} > \overline{h_{4,4}}$, suggesting KRW/USD future market's the strongest own effects. For the cross-volatility spillovers, we see that $\overline{h_{1,3}} > \overline{h_{2,3}} > \overline{h_{2,4}} > \overline{h_{3,4}} > \overline{h_{1,2}} > \overline{h_{1,4}} > \overline{h_{1,3}} > \overline{h_{2,3}}$. The above results reveal that cross-spillover effects for the pairs of markets JPY/USD-EUR/USD ($\overline{h_{1,3}}$) and KRW/USD- EUR/USD ($\overline{h_{2,3}}$) are relatively stronger. All the cross-volatility spillovers are approximately the same, indicating a level of integration and interdependence.

In Appendix D, we present the conditional variances for INR/USD, JPY/USD, KRW/USD and EUR/USD. All markets demonstrate high levels of volatility. Interestingly, we observe time varying levels of fluctuations.

Conditional covariances are presented below in figure 2. We observe that conditional covariances for the pairs of markets JPY/USD-EUR/USD, KRW/USD-EUR/USD and KRW/USD-INR/USD have only positive values. In addition, we notice mostly positive values for the conditional covariances for the pairs of markets JPY/USD-KRW/USD, JPY/USD-INR/USD and EUR/USD-INR/USD.

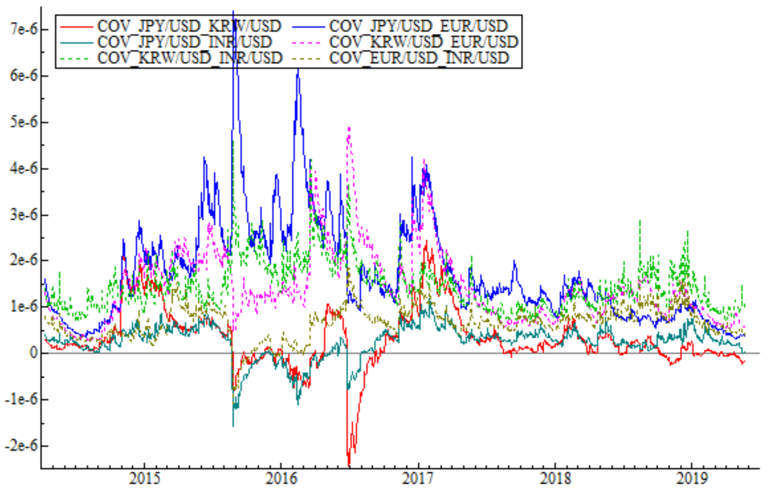

Figure 2: Conditional covariances of the fourvariate FIGARCH(1,d,1)-cDCC model

Notes: Data from Datastream. The red lines represent the conditional covariances of the fourvariate conditional variance matrix (H_t) for all the pairs of markets, generated by Equation 4.

5.4. Dynamic Conditional Correlations Characteristics

Appendix E reports the descriptive statistics of the dynamic conditional correlations (DCCs) of the six pairs of markets generated by Equation 5. The highest mean value (0,83398) is observed between JPY/USD and EUR/USD. Moreover, the DCC between KRW/USD and EUR/USD experiences larger fluctuations considering the the second highest maximum value (4,9157e-006) and the highest std. deviation value (7,7824e-007). The Skewness, Excess Kyrtosis and the Jarque-Bera test statistics indicate that the DCCs for all the pairs of markets are not normally distributed. Based on Figure 3 below, we analyze the pair-wise DCCs as follows.

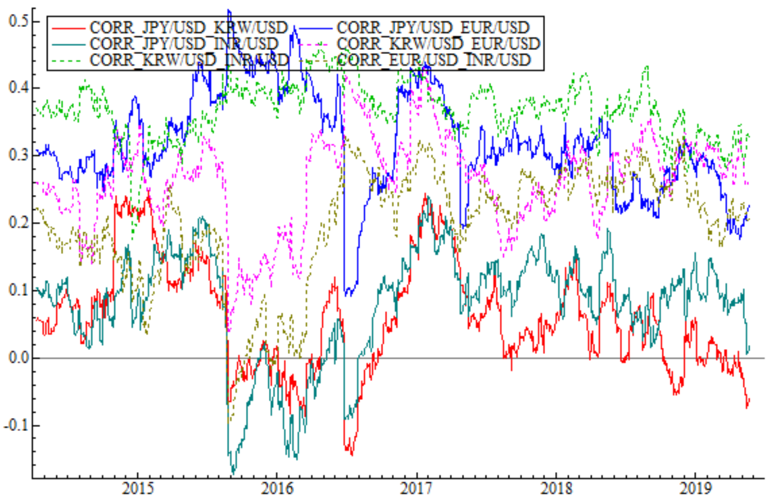

Figure 3: Dynamic Conditional Correlations of the Fourvariate FIGARCH(1,d,1)-cDCC Mode.l

Notes: Data from Datastream. The red lines illustrate the dynamic conditional correlations (R_t), generated by Equation 6 for all the pairs of markets.

DCCs for the pairs of markets JPY/USD-KRW/USD, JPY/USD-INR/USD and EUR/USD-INR/USD have mostly positive values and are extremely volatile, suggesting risky correlations from an investor’s perspective. Additionally, we can clearly recognize the effects of major economic events on the graphs, i.e. (a) the BOJ announcement of a massive easing program (30/03/2015), (b) the black Monday (24/08/2015), (c) the United Kingdom referendum

(23/06/2016), and (d) the French Presidential elections (23/04/2017), among others.

Next, DCCs for the pairs of markets JPY/USD-EUR/USD, KRW/USD-EUR/USD and KRW/USD-INR/USD have positive values and extreme volatility levels, indicating risky correlations for any investor. Moreover, we see on the graphs the effects of major economic events, i.e. (a) the President of the Catalonia announcement for a referendum on independence on 9/11/2014 from Spain (14/10/2014), (b) the European Central Bank announcement of an aggressive money-creation program (22/01/2015), (c) Black Monday (24/08/2015), and (d) the United Kingdom referendum (23/06/2016), among others.

6. Conclusions

This paper investigates the potential spillovers and contagion among the JPY/USD, KRW/USD, EUR/USD and INR/USD futures FOREX markets. Specifically, we quantify volatility transmission by employing a fourvariate cDCC- FIGARCH(1,d,1) model. The under investigation period is from 2014 until 2019. To the best of our knowledge, this is the first empirical study, investigating volatility spillover effects among major futures FOREX markets.

We find interesting results. Spearman's rank correlation results reveal the highest rank correlation for KRW/USD-INR/USD and JPY/USD-EUR/USD, revealing a level of integration for the above markets. The mean values of conditional variances and covariances show that KRW/USD demonstrates the highest own volatility, showing that KRW/USD is the most immune futures market. Results indicate strong evidence of volatility spillover effects. Based on DCCs, results state significant evidence of contagion effects for all the pairs of markets. DCCs have mostly negative values during the mid-2015 until mid-2016 for the pairs of markets JPY/USD-KRW/USD and JPY/USD-INR/USD, presenting no contagion effects.

A natural extension to this article would be to investigate the potential contagion mechanisms during the period 2007-2012 global financial crises. In particular, we focus on the revelation of possible contagion effects among JPY/USD, KRW/USD, EUR/USD and INR/USD futures markets.

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APPENDIX A

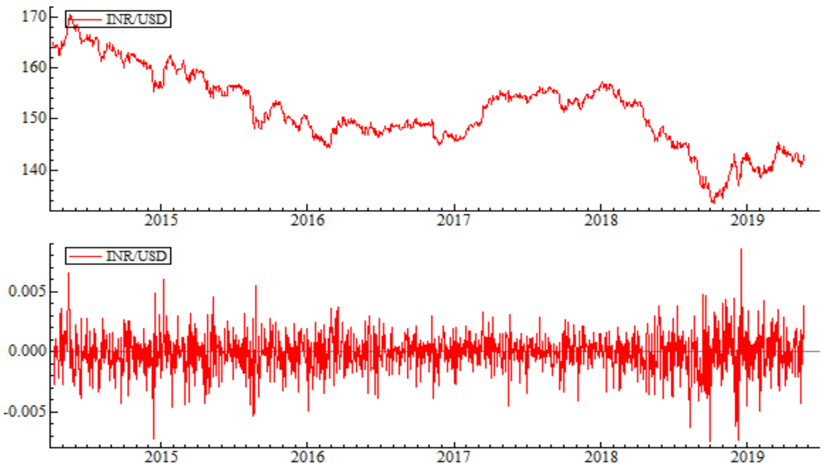
Summary Statistics of Daily Market Futures' Returns, Sample Period: 9th April, 2014 – 21st May, 2019

	JPY/USD	KRW/USD	EUR/USD	INR/USD
Panel A: descriptive statistics				
Mean	-2,6349e-005	-4,4291e-005	-6,8615e-005	-4,6893e-005
Minimum	-0,011822	-0,010527	-0,010582	-0,0074038
Maximum	0,015012	0,01172	0,012647	0,0086038
Std. Deviation	0,0023655	0,0022946	0,0022172	0,0016445
Panel B: Normality Test				
Skewness	0,50830***	0,28471***	0,12016	-0,21557***
t-Statistic	7,5877	4,2501	1,7937	3,2179
p-Value	3,2567e-014	2,1367e-005	0,072860	0,0012912
Excess Kyrtosis	4,7338***	2,0156***	2,6551***	1,9391***
t-Statistic	35,358	15,055	19,832	14,484
p-Value	7,4779e-274	3,1949e-051	1,5729e-087	1,5327e-047
Jarque-Bera	1303,0	243,83	395,06	219,33
p-Value	1,1458e-283	1,1272e-053	1,6390e-086	2,3592e-048
Panel C: Unit Root Test				
ADF	-20,3041	-21,94	-21,7905	-23,0789
Critical value: 1%	-2,56572	-2,56572	-2,56572	-2,56572
Critical value: 5%	-1,94093	-1,94093	-1,94093	-1,94093
Critical value: 10%	-1,61663	-1,61663	-1,61663	-1,61663
Panel D: ARCH-Lagrange Multiplier test				
ARCH 1-2 test	9,8475**	5,5265**	11,578**	14,197**
	0,0000	0,0000	0,0000	0,0000
ARCH 1-5 test	5,2953**	4,6381**	8,7785**	7,2703**
	0,0000	0,0000	0,0000	0,0000
ARCH 1-10 test	3,6284**	4,9085**	7,5456**	5,4532**
	0,0000	0,0000	0,0000	0,0000
Panel E: GPH long memory test				
d	0,0312811	-0,0387445	-0,0153296	-0,0473552
p-Value	0,2406	0,1500	0,5649	0,0739

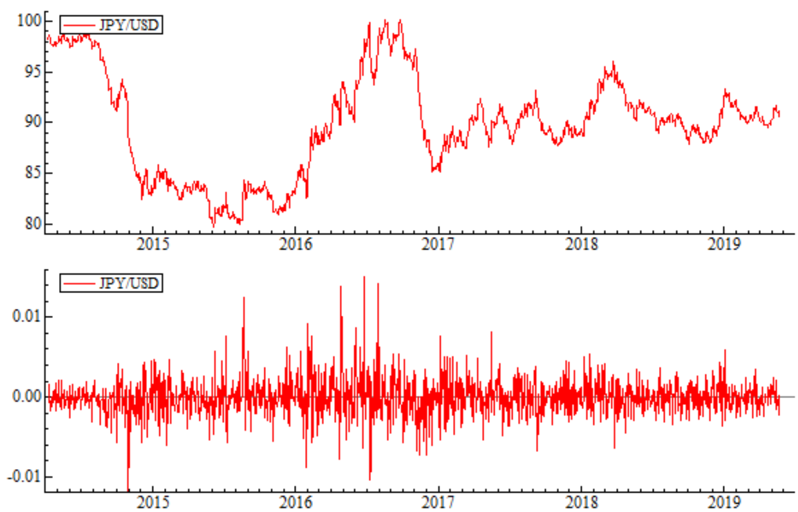
Notes. Panel A presents the descriptive statistics. Panel B shows the normality test. Panel C demonstrates the unit root tests. We used intercept and a time trend to generate the ADF statistic. Panel D reveals the ARCH-Lagrange Multiplier test. In Panel E we observe the Autocorrelation and long-term dependence tests. ** and *** signify statistical significance at the 5% and 1% levels, respectively.

APPENDIX B

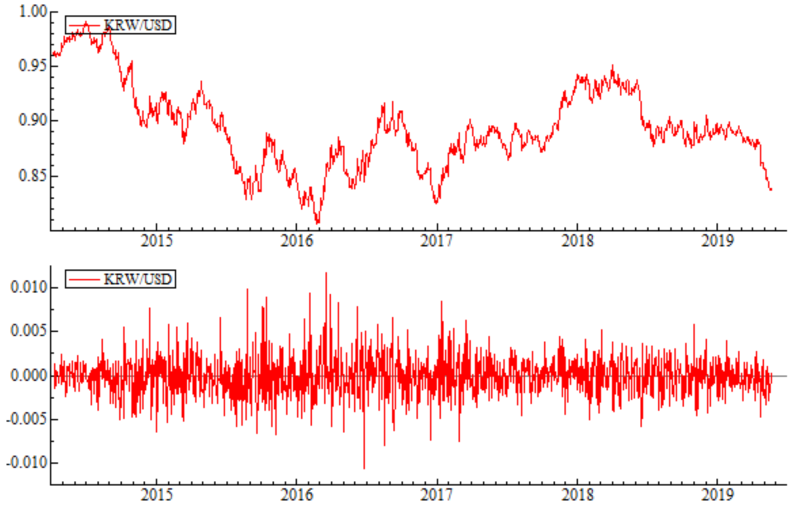
Actual series of future markets and their respective logarithmic returns.



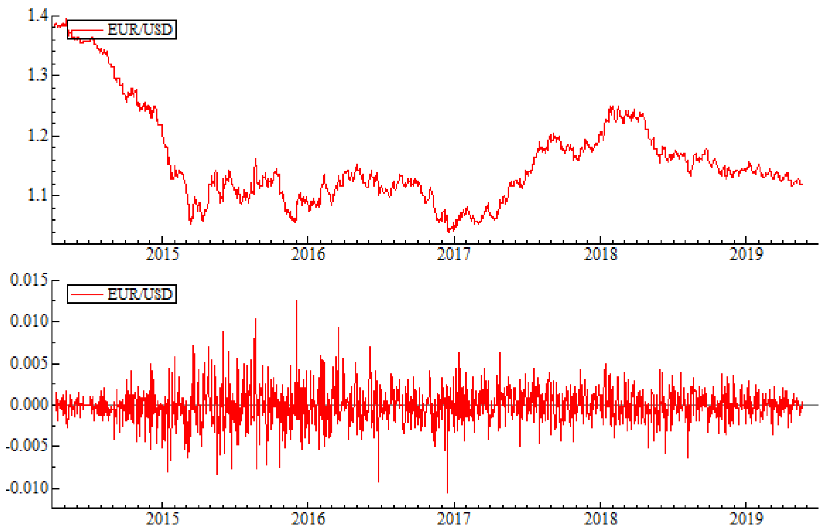
Graph A. INR/USD



Graph B. JPY/USD



Graph C. KRW/USD



Graph D. EUR/USD

Notes. Data from Datastream. We calculate future market returns using the equation: $r_t = log(p_t) - log(p_{t-1})$.

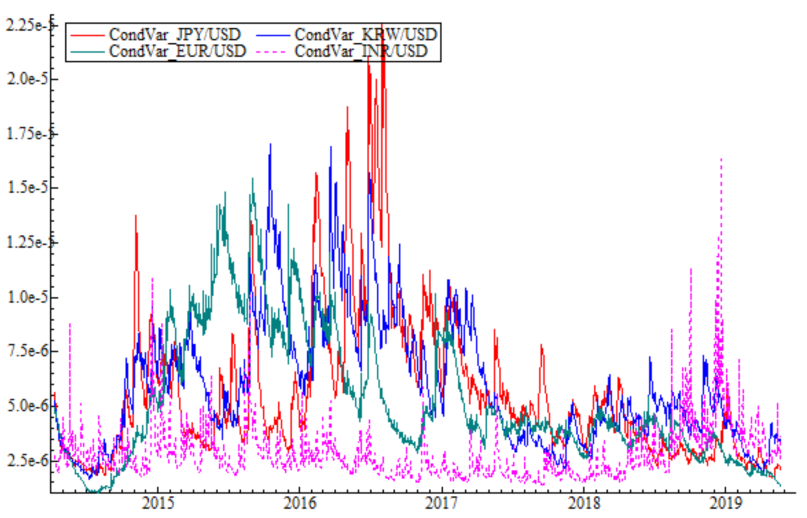
APPENDIX C

Mean values of Conditional Variances and Covariances ($\overline{h_{\iota,j}}$), Sample Period: 9th April, 2014 – 21st May, 2019

Market i	JPY/USD (i=1)	KRW/USD (i=2)	EUR/USD (i=3)	INR/USD (i=4)
$(\overline{h_{\iota,1}})$	5,5701e-006			
$(\overline{h_{\iota,2}})$	2,9029e-007	5,9428e-006		
$(\overline{h_{\iota,3}})$	1,731e-006	1,4039e-006	5,2424e-006	
$(\overline{h_{\iota,4}})$	2,5169e-007	1,331e-006	6,2839e-007	2,7766e-006

Note: $\overline{h_{\iota,j}}$, with i, j = 1,…,N, denotes the mean values of conditional variances and conditional covariances.

APPENDIX D
Conditional Variances of the Univariate FIGARCH(1,d,1) Model



Notes. Data from Datastream. The red lines represent the conditional variances for all future markets, generated by Equation 3.

APPENDIX E

Statistical Properties of the Fourvariate FIGARCH-cDCC's, Sample Period: 9th April, 2014 – 21st May, 2019

	JPY/USD-KRW/USD	JPY/USD-EUR/USD	JPY/USD-INR/USD	KRW/USD-EUR/USD	KRW/USD-INR/USD	EUR/USD-INR/USD
Panel A: descriptive statistics						
Mean	2,9029e-007	1,731e-006	2,5169e-007	1,4039e-006	1,331e-006	6,2839e-007
Minimum	-2,6937e-006	3,2753e-007	-1,3828e-006	2,5462e-007	6,2181e-007	-1,0314e-006
Maximum	2,4171e-006	7,431e-006	1,1353e-006	4,9157e-006	4,5923e-006	1,8578e-006
Std. Deviation	6,3098e-007	1,1258e-006	3,4707e-007	7,7824e-007	4,855e-007	3,4448e-007
Panel B: Normality Test						
Skewness	-0,041146	1,5123***	-1,3048***	1,2670***	1,4296***	-0,33267***
t-Statistic	0,61421	22.575	19,477	18,913	21,340	4,9660
p-Value	0,53907	7,6445e-113	1,7132e-084	8,9872e-080	4,8098e-101	6,8339e-007
Excess Kyrtosis	3,6231***	3,1316***	2,8093***	2,1319***	3,7631***	2,1703***
t-Statistic	27,062	23,391	20,983	15,924	28,108	16,211
p-Value	2,7343e-161	5,2773e-121	9,3191e-098	4,3061e-057	7,7916e-174	4,2130e-059
Jarque-Bera	730,02	1053,6	817,17	609,52	1241,5	286,42
p-Value	3,0136e-159	1,6496e-229	3,5814e-178	4,4161e-133	2,5754e-270	6,3639e-063

Notes: Panel A presents the descriptive statistics. Panel B shows the normality test. *** signify statistical significance at 1% level.

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