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On the Co-movements among East Asian Foreign Exchange Markets: A Multivariate FIAPARCH-DCC approach

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Abstract

This study examines the interdependence of six daily East Asian exchange rates: INR (Indonesia), SGD (Singapore), THB (Thailand), KRW (South Korea), PHP (Philippine) and MYR (Malaysia) expressed in US dollar. Focusing on different phases of the global financial and Asian crises, the aim of this paper is to examine how the dynamics of correlations between East Asian exchange markets evolved from January 01, 1995 to September 30, 2015. To this end, we adopt a dynamic conditional correlation (DCC) model into a multivariate Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) framework, which accounts for long memory, power effects, leverage terms and time varying correlations. The empirical findings indicate a general pattern of decrease in exchange rates correlations during the phase of recession and the first phase of the global financial crisis, suggesting the depreciation against US dollar and different vulnerability of the currencies.

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1. Introduction

Unlike past crises, such as the 1997 Asian financial crisis, the 1998 Russian crisis and the 1999 Brazilian crisis, the recent 2007-2009 global financial crisis originated from the largest and most influential economy, the US market, and was spreading over the other countries' financial markets worldwide. Global financial crisis resulted in sharp declines in asset prices, stock and foreign exchange markets, and skyrocketing of risk premiums on interbank loans. It also disrupted country's financial system and threatened real economy with huge contractions.

The effect of global financial crisis on stock, bond and other asset markets have analyzed by Arghyrou and Kontonikas (2012), Baur (2012), Chan et al. (2011), Guo et al. (2011), Kenourgios and Padhi (2012) and Dimitriou et al. (2013). Since, the growing significance of the Asian share in world trade and capital mobility, and the rapid growth in their domestic market capitalization over the past few decades (see Kohsaka 2004), Asian financial markets has prompted researchers, policy makers as well as analysts to carry out detailed analysis of the interaction among the exchange rate market. The importance of modeling currency is supported by Dungey and Martin (2007), Lin (2011), and Tsai (2012).

Nevertheless, studies that examine the behavior of exchange rates during those crisis periods are still rare (see Dimitriou and Kenourgios, 2013). These crises therefore provide a unique natural experiment for investigating the dynamic interrelationships among international foreign exchange markets, which have many implications for international asset pricing and portfolio allocation as well as for policy makers to develop strategies to insulate economies.

Since the seminal work of Engle et al. (1990), there is prior literature investigating the volatility spillover linkages among foreign exchange markets. Engle et al. (1990) show that the uncertainty in exchange rates arises not only from local shocks, but also transmitted across markets. The volatility spillovers among currencies have been analyzed using conventional methodologies, such as cointegration, causality, GARCH specifications and cross-correlation function (see Nikkinen et al., 2006; Inagaki, 2007, among others). Nevertheless, this literature suffers from certain drawbacks. First, the possibility of non-normality and asymmetry in the variance of returns has not been captured by the cointegration approach (see Baele, 2005). Second, when measuring correlations caused by volatility increases during a crisis, there is a heteroskedasticity problem (see Forbes and Rigobon, 2002). Third, most of the GARCH family models assume that correlation coefficients are constant over time (see Bollersev, 1990), while their multivariate variants suffer from the curse of dimensionality (see Engle, 2002). Fourth, the second moments of correlations and covariances must be examined in order to provide evidence of dynamic changes in linkages among markets across stable and crisis periods (see Pesaran and Pick, 2007).

To circumvent the drawbacks of this literature, recent research on exchange rates linkages focuses on their dynamic conditional correlations in a time-varying GARCH framework (see Engle and Sheppard, 2001; Tse and Tsui, 2002; Engle, 2002). In this article, we focus on interrelations between the returns on the market for foreign exchange in six East Asian countries in the period during the Asian financial crises in the period 1997–1998 and the Global Financial Crisis in 2008–2009 that originated in the United States. Specifically, we empirically investigate the time-varying linkages of six East Asian exchange rates, namely Indonesia (INR), Singapore (SGD), South Korean won (KRW), Taiwan (THB), Philippine (PHP) and Malaysia (MYR) expressed in US dollar from January 01, 1995 until September 30, 2015. We use a DCC model into a multivariate fractionally integrated APARCH framework (FIAPARCH-DCC model), which provides the tools to understand how financial volatilities move together over time and across markets. Conrad et al. (2011) applied a multivariate fractionally integrated asymmetric power ARCH (FIAPARCH) model that combines long memory, power transformations of the conditional variances, and leverage effects with constant conditional correlations (CCC) on eight national stock market indices returns. The long-range volatility dependence, the power transformation of returns and the asymmetric response of volatility to positive and negative shocks are three features that improve the modeling of the volatility process of asset returns. We extend their model by estimating time varying conditional correlations among the currencies and then examine the dynamic patterns of correlation changes across the phases of the Asian and global financial crises. The GARCH model analyzes the symmetric effect of volatility and the EGARCH model analyzes the asymmetric effect in the context of short memory. However, the FIAPARCH model detects the asymmetric effect in the context of long memory.

From an economic perspective, monetary authorities may intervene so as to maintain price stability and competitiveness in exports, when other currencies depreciate or appreciate (see Dimitriou and Kenourgios, 2013). This behavior may cause different degrees of exchange rates co-movements during crisis periods compared to stable periods. For that reason, it would be useful to empirically examine the dynamic dependence structure of international emerging exchange markets during an unstable period which covers two of the most severe financial and economic crises occurred the last decades.

The present study provides a robust analysis of dynamic linkages among exchange markets that goes beyond a simple analysis of correlation breakdowns. The time-varying DCCs are captured from a multivariate student-t-FIAPARCH-DCC model which takes into account long memory behavior, speed of market information, asymmetries and leverage effects.

The rest of the paper is organized as follows. Section 2 presents the econometric methodology. Section 3 provides the data and a preliminary analysis. Section 4 displays and discusses the empirical findings and their interpretation, while section 5 provides our conclusions.

2. Econometric methodology

The present study investigates the dynamics correlations among East Asian foreign exchange market from January 01, 1995 until September 30, 2015. We provide a robust analysis of dynamic linkages among exchange markets that goes beyond a simple analysis of correlation breakdowns. The time-varying DCCs are captured from a multivariate student-t-FIAPARCH-DCC model which takes into account long memory behavior, asymmetries and leverage effects. (equations of the univariate and multivariate FIAPARCH model are detailed in appendix 1).

3. Data and preliminary analyses

The data comprises daily East Asian exchange rates: INR (Indonesia), SGD (Singapore), THB (Thailand), KRW (South Korea), PHP (Philippine) and MYR (Malaysia) expressed in US dollar. All data are sourced from the (http//www.Federalreserves.gov). The sample covers a period from January 01, 1995 until September 30, 2015, leading to a sample size of 7578 observations. For each exchange rates, the continuously compounded return is computed as $r_t = 100 \times \ln(p_t/p_{t-1})$ for $t = 1,2,\ldots,T$, where $p_t$is the price on day t.

Summary statistics for the exchange market returns are displayed in Table 1(Panel A, appendix 2). From these tables, KRW/USD is the most volatile, as measured by the standard deviation of 0.7535%, while PHP/USD is the least volatile with a standard deviation of 0.0245%. Besides, we observe that THB/USD has the highest level of excess kurtosis, indicating that extreme changes tend to occur more frequently for the exchange rate. In addition, all exchange market returns exhibit high values of excess kurtosis. To accommodate the existence of "fat tails", we assume student-t distributed innovations. Furthermore, the Jarque-Bera statistic rejects normality at the 1% level for all exchange rate. Moreover, all exchange market return series are stationary, I(0), and thus suitable for long memory tests. Finally, they exhibit volatility clustering, revealing the presence of heteroskedasticity and strong ARCH effects.

In order to detect long-memory process in the data, we use the log-periodogram regression (GPH) test of Geweke and Porter-Hudak (1983) on two proxies of volatility, namely squared returns and absolute returns. The test results are displayed in Table 1 (Panel D). Based on these tests' results, we reject the null hypothesis of no long-memory for absolute and squared returns at 1% significance level. Subsequently, all volatilities proxies seem to be governed by a fractionally integrated process. Thus, FIAPARCH seem to be an appropriate specification to capture volatility clustering, long-range memory characteristics and asymmetry.

4. Empirical results

4.1. The univariate FIAPARCH estimates

In order to take into account the serial correlation and the GARCH effects observed in our time series data, and to detect the potential long range dependence in volatility, we estimate the student[1]-t-AR(0)-FIAPARCH(1,d,1)[2] model defined by Eqs. (1) and (5) (see appendix 1). Table 2 (see Appendix 2) reports the estimation results of the univariate FIAPARCH(1,d,1) model for each exchange market return series of our sample.

The estimates of the constants in the mean are statistically significant at 1% level or better for all the series. Besides, the constants in the variance are no significant for all series. In addition, for all currencies, the estimates of the leverage term (γ) are statistically significant, indicating an asymmetric response of volatilities to positive and negative shocks. This finding confirms the assumption that there is negative correlation between returns and volatility. According to Patton (2006), such asymmetric effects could be explained by the asymmetric behavior of central banks in their currency interventions. In other words, Patton (2006) argues that when central banks emphasize on competitiveness over price stability, the exchange rates may display higher volatility during periods of depreciation compared to periods of appreciation.

Moreover, the estimates of the power term (δ) are highly significant for all currencies and ranging from 0.0368 to 2.0889. Conrad et al. (2011) show that when the series are very likely to follow a non-normal error distribution, the superiority of a squared term ($\delta = 2$) is lost and other power transformations may be more appropriate. Thus, these estimates support the selection of FIAPARCH model for modeling conditional variance of exchange market returns. Besides, all exchange rate display highly significant differencing fractional parameters(d), indicating a high degree of persistence behavior. This implies that the impact of shocks on the conditional volatility of exchange market' returns consistently exhibits a hyperbolic rate of decay. Interestingly, the highest power term is obtained for INR/USD exchange rate, one is characterized by the highest degree of persistence. In all cases, the estimated degrees of freedom parameter (v) is highly significant and leads to an estimate of the Kurtosis which is equal to $3(\text{v}-2)/(\text{v}-4)$ and is also different from three.

In addition, all the ARCH parameters (ϕ) satisfy the set of conditions which guarantee the positivity of the conditional variance. Moreover, according to the values of the Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, there is no statistically significant evidence, at the 1% level, of misspecification in almost all cases except for the SGD/USD and KRW/USD exchange rates.

Numerous studies have documented the persistence of volatility in stock and exchange rate returns (see Ding et al., 1993; Ding et Granger, 1996, among others).The majority of these studies have shown that the volatility process is well approximated by an IGARCH process. Nevertheless, from the FIAPARCH estimates reported in Table 3, it appears that the long-run dynamics are better modeled by the fractional differencing parameter.

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[1] The z_t random variable is assumed to follow a student distribution (see Bollerslev, 1987) with $\upsilon > 2$ degrees of freedom and with a density given by:

$$D(z_t,\upsilon) = \frac{\Gamma(\upsilon+\frac{1}{2})}{\Gamma(\frac{\upsilon}{2})\sqrt{\pi(\upsilon-2)}}(1+\frac{z_t^2}{\upsilon-2})^{\frac{1}{2}-\upsilon}$$

where$\Gamma(\upsilon)$ is the gamma function and υ is the parameter that describes the thickness of the distribution tails. The Student distribution is symmetric around zero and, for $\upsilon > 4$, the conditional kurtosis equals $3(\upsilon-2)/(\upsilon-4)$, which exceeds the normal value of three. For large values of υ, its density converges to that of the standard normal.

For a Student-*t* distribution, the log-likelihood is given as: $L_{Student} = T\left\{log\Gamma\left(\frac{\upsilon+1}{2}\right) - log\Gamma\left(\frac{\upsilon}{2}\right) - \frac{1}{2}log[\pi(\upsilon-2)]\right\} - \frac{1}{2}\sum_{t=1}^{T}\left[\log(h_t) + (1+\upsilon)log\left(1+\frac{z_t^2}{\upsilon-2}\right)\right]$

where$T$ is the number of observations, υ is the degrees of freedom, $2 < \upsilon \leq \infty$ and $\Gamma(.)$ is the gamma function.

[2] The lag orders$(1, d, 1)$and (0,0) for FIAPARCH and ARMA models, respectively, are selected by Akaike (AIC) and Schwarz (SIC) information criteria. The results are available from the author upon request.

4.2. The bivariate FIAPARCH(1,d,1)-DCC estimates

The analysis above suggests that the FIAPARCH specification describes the conditional variances of the six exchange rate well. Therefore, the multivariate FIAPARCH model seems to be essential for enhancing our understanding of the relationships between the (co)volatilities of economic and financial time series.

In this section, within the framework of the multivariate DCC model, we analyze the dynamic adjustments of the variances for the all exchange rate. Overall, we estimate nine bivariate / multivariate specifications for our analysis (n>=2). Table 3, 4, 5 and 6 (Panels A and B) (see appendix 3) reports the estimation results of the bivariate student-t-FIAPARCH(1,d,1)-DCC model. The ARCH and GARCH parameters (a and b) of the DCC(1,1) model capture, respectively, the effects of standardized lagged shocks and the lagged dynamic conditional correlations effects on current dynamic conditional correlation. They are statistically significant at the 5% level, indicating the existence of time-varying correlations. Moreover, they are non-negative, justifying the appropriateness of the FIAPARCH model. When $a = 0$ and $b = 0$, we obtain the Bollerslev's (1990) Constant Conditional Correlation (CCC) model. As shown in Tables 3, 4, 5 and 6, the estimated coefficients a and b are significantly positive and satisfy the inequality $a + b < 1$ in each of the pairs of exchange rates. Besides, the t-student degrees of freedom parameter (v)is highly significant, supporting the choice of this distribution.

The statistical significance of the DCC parameters (a and b) reveals a considerable time-varying co-movement and thus a high persistence of the conditional correlation. The sum of these parameters is close to unity. This implies that the volatility displays a highly persistent fashion. Since $a + b < 1$, the dynamic correlations revolve around a constant level and the dynamic process appears to be mean reverting. The multivariate FIAPARCH-DCC model is so important to consider in our analysis since it has some key advantages. First, it captures the long range dependence property. Second, it allows obtaining all possible pair-wise conditional correlation coefficients for the exchange market returns in the sample. Third, it's possible to investigate their behavior during periods of particular interest, such as periods of the global financial and Asian crises. Fourth, the model allows looking at possible financial contagion effects between international foreign exchange markets.

Finally, it is crucial to check whether the selected exchange rate series display evidence of multivariate Long Memory ARCH effects and to test ability of the Multivariate FIAPARCH specification to capture the volatility linkages among exchange rate. Kroner and Ng (1998) have confirmed the fact that only few diagnostic tests are kept to the multivariate GARCH-class models compared to the diverse diagnostic tests devoted to univariate counterparts. Furthermore, Bauwens et al. (2006) have noted that the existing literature on multivariate diagnostics is sparse compared to the univariate case. In our study, we refer to the most broadly used diagnostic tests, namely the Hosking's and Li and McLeod's Multivariate Portmanteau statistics on both standardized and squared standardized residuals. According to Hosking (1980), Li and McLeod (1981) and McLeod and Li (1983) autocorrelation test results reported in Tables 3, 4, 5 and 6 (Panel B, Appendix 3), the multivariate diagnostic tests allow accepting the null hypothesis of no serial correlation on squared standardized residuals and thus there is no evidence of statistical misspecification.

Fig. 1 (see Appendix 4) illustrates the evolution of the estimated dynamic conditional correlations dynamics among East Asian exchange markets. Compared to the pre-crises period, the estimated DCCs show a decline during the post-crises period. Such evidence is in contrast with the findings of previous research on foreign exchange markets, which show increases in correlations during periods of financial turmoil (see Kenourgios et al., 2011; Dimitriou et al., 2013; Dimitriou and Kenourgios, 2013). Nevertheless, the different path of the estimated DCCs displays fluctuations for all pairs of exchange rates across the phases of the Asian and global financial crises, suggesting that the assumption of constant correlation is not appropriate. The above findings motivate a more extensive analysis of DCCs, in order to capture contagion dynamics during different phases of the two crises.

5. Conclusions and policy implications

The present study contributes to the literature on co-movements among East Asian exchange rates. It examines the time-varying linkages among daily East Asian exchange rates: INR (Indonesia), SGD (Singapore), THB (Thailand), KRW (South Korea), PHP (Philippine) and MYR (Malaysia) expressed in US dollar. Specifically, we employ a multivariate FIAPARCH-DCC approach during the period from January 01, 1995 to September 30, 2015, focusing on the estimated dynamic conditional correlations among the currencies. The FIAPARCH-DCC approach allows investigating the second order moment's dynamics of exchange rates taking into account long range dependence behavior, asymmetries and leverage effects.

The negative correlations among the foreign exchange market during the period of the Asian crisis are related to the Asian miracle. The world capital markets over invested in the Asian economies. This investment boom represented a significant positive shock to these economies, contributing to asset price increases, especially in the stock market. Corsetti et al. (1999) conclude that, despite the liberalization of internal and external financial control in the 1990s that triggered this boom, most of the Asian economies pursued a policy of an effective peg to the U.S. dollar in order to facilitate and maintain external financing of domestic investments. The peg reduced the currency risk premium charged by international investors. When the U.S. dollar strengthened, the value of the Asian currencies per U.S. dollar soared in 1996. This domestic currency appreciation eroded competitiveness in the traded-goods sector causing a shift in the composition of capital inflows from foreign direct investment to more liquid portfolio investment.

The empirical findings could lead to important implications from investors' and policy makers' perspective. The decline of exchange rates linkages during crisis periods shows the different vulnerability of the currencies and implies an increase of portfolio diversification benefits, since holding a portfolio with diverse currencies is less subject to systematic risk (see Dimitriou and Kenourgios, 2013). Moreover, Dimitriou and Kenourgios (2013) argue that this correlations' behavior may be considered as evidence of non-cooperative monetary policies around the world and highlight the need for some form of policy coordination among central banks. In addition, these authors argue that the different patterns of dynamic linkages among international currencies could influence transnational trade flows and the activities of multinational corporations, as they create uncertainty with regard to exports and imports.

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Appendix 1

Univariate FIAPARCH model

The AR(1) process represents one of the most common models to describe a time series r_t of stock returns and foreign exchange rate. Its formulation is given as

$$(1-\xi L)r_t = c + \varepsilon_t, \quad t \in \mathbb{N} \tag{1}$$

with

$$\varepsilon_t = z_t\sqrt{h_t} \tag{2}$$

where $|c| \in [0, +\infty[$, $|\xi| < 1$ and $\{z_t\}$ are independently and identically distributed $(i.i.d.)$ random variables with $E(z_t) = 0$. The variance h_t is positive with probability equal to unity and is a measurable function of Σ_{t-1} , which is the $\sigma -$algebra generated by $\{r_{t-1}, r_{t-2}, \ldots\}$. Therefore, h_t denotes the conditional variance of the returns $\{r_t\}$, that is:

$$E[r_t/\Sigma_{t-1}] = c + \xi r_{t-1} \tag{3}$$

$$Var[r_t/\Sigma_{t-1}] = h_t \tag{4}$$

Tse (1998) uses a FIAPARCH(1,d,1) model in order to examine the conditional heteroskedasticity of the yen-dollar exchange rate. Its specification is given as

$$(1-\beta L)\left(h_t^{\delta/2} - \omega\right) = [(1-\beta L) - (1-\phi L)(1-L)^d](1+\gamma s_t)|\varepsilon_t|^\delta \tag{5}$$

where $\omega \in [0, \infty[$, $|\beta| < 1$, $|\phi| < 1$, $0 \le d \le 1$, $s_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise, $(1-L)^d$ is the financial differencing operator in terms of a hypergeometric function (see Conrad et al., 2011), γ is the leverage coefficient, and δ is the power term parameter (a Box-Cox transformation) that takes (finite) positive values. A sufficient condition for the conditional variance h_t to be positive almost surely for all t is that $\gamma > -1$ and the parameter combination (ϕ, d, β) satisfies the inequality constraints provided in Conrad and Haag (2006) and Conrad (2010).When $\gamma > 0$, negative shocks have more impact on volatility than positive shocks.

The advantage of this class of models is its flexibility since it includes a large number of alternative GARCH specifications. When $d = 0$, the process in Eq. (5) reduces to the APARCH(1,1) one of Ding et al. (1993), which nests two major classes of ARCH models. In particular, a Taylor/Schwert type of formulation (Taylor, 1986; Schwert, 1990)is specified when $\delta = 1$, and a Bollerslev(1986) type is specified when $\delta = 2$. When $\gamma = 0$and $\delta = 2$, the process in Eq. (5) reduces to the $FIGARCH(1, d, 1)$ specification (see Baillie et al., 1996; Bollerslev and Mikkelsen, 1996) which includes Bollerslev's (1986) GARCH model (when $d = 0$) and the IGARCH specification (when $d = 1$) as special cases.

Multivariate FIAPARCH model with dynamic conditional correlations

In what follow, we introduce the multivariate FIAPARCH process (M-FIAPARCH) taking into account the dynamic conditional correlation (DCC) hypothesis (see Dimitriou et al., 2013) advanced by Engle (2002). This approach generalizes the Multivariate Constant Conditional Correlation (CCC) FIAPARCH model of Conrad et al. (2011). The multivariate DCC model of Engle (2002) and Tse and Tsui (2002)involves two stages to estimate the conditional covariance matrix H_t. In the first stage, we fit a univariate FIAPARCH(1,d,1) model in order to obtain the estimations of $\sqrt{h_{iit}}$. The daily returns of exchange rate are assumed to be generated by a multivariate AR(1) process of the following form:

$$Z(L)r_t = \mu_0 + \varepsilon_t \tag{6}$$

where

- $\mu_0 = [\mu_{0,i}]_{i=1,\dots,n}$: the N −dimensional column vector of constants;
- $|\mu_{0,i}| \in [0, \infty[$;
- $Z(L) = diag\{\psi(L)\}$: an $N \times N$ diagonal matrix ;
- $\psi(L) = [1 - \psi_i L]_{i=1,\dots,n}$;
- $|\psi_i| < 1$;
- $r_t = [r_{i,t}]_{i=1,\dots,N}$: the N −dimensional column vector of returns;
- $\varepsilon_t = [\varepsilon_{i,t}]_{i=1,\dots,N}$: the$N$ −dimensional column vector of residuals.

The residual vector is given by

$$\varepsilon_t = z_t \odot h_t^{\wedge 1/2} \tag{7}$$

where

- $\odot$: the Hadamard product;
- $\wedge$: the elementwise exponentiation.

$h_t = [h_{it}]_{i=1,\dots,N}$ is Σ_{t-1} measurable and the stochastic vector $z_t = [z_{it}]_{i=1,\dots,N}$ is independent and identically distributed with mean zero and positive definite covariance matrix $\rho = [\rho_{ijt}]_{i,j=1,\dots,N}$ with $\rho_{ij} = 1$ for $i = j$.Note that $E(\varepsilon_t/\mathcal{F}_{t-1}) = 0$and $H_t = E(\varepsilon_t\varepsilon_t'/\mathcal{F}_{t-1}) = diag(h_t^{\wedge 1/2})\,\rho\, diag(h_t^{\wedge 1/2})$. h_t is the vector of conditional variances and $\rho_{i,j,t} = h_{i,j,t}/\sqrt{h_{i,t}h_{j,t}} \forall\, i,j = 1,\dots,N$ are the dynamic conditional correlations.
The multivariate FIAPARCH(1,d,1) is given by

$$B(L)\left(h_t^{\wedge\delta/2} - \omega\right) = [B(L) - \Delta(L)\Phi(L)][\mathrm{I}_N + \Gamma_t]|\varepsilon_t|^{\wedge\delta} \tag{8}$$

where$|\varepsilon_t|$ is the vector ε_t with elements stripped of negative values.

Besides, $B(L) = diag\{\beta(L)\}$ with $\beta(L) = [1 - \beta_i L]_{i=1,\dots,N}$ and $|\beta_i| < 1$. Moreover, $\Phi(L) = diag\{\phi(L)\}$ with $\phi(L) = [1 - \phi_i L]_{i=1,\dots,N}$and $|\phi_i| < 1$. In addition, $\omega = [\omega_i]_{i=1,\dots,N}$ with $\omega_i \in [0, \infty[$ and $\Delta(L) = diag\{d(L)\}$ with $d(L) = [(1-L)^{d_i}]_{i=1,\dots,N}$ $\forall\, 0 \le d_i \le 1$. Finally, $\Gamma_t = diag\{\gamma \odot s_t\}$ with $\gamma = [\gamma_i]_{i=1,\dots,N}$ and $s_t = [s_{it}]_{i=1,\dots,N}$ where $s_{it} = 1$ if $\varepsilon_{it} < 0$ and 0 otherwise.

In the second stage, we estimate the conditional correlation using the transformed exchange returns residuals, which are estimated by their standard deviations from the first stage. The multivariate conditional variance is specified as follows:

$$H_t = D_t R_t D_t \tag{9}$$

where $D_t = diag\left(h_{11t}^{1/2}, \ldots, h_{NNt}^{1/2}\right)$ denotes the conditional variance derived from the univariate AR(1)-FIAPARCH(1,d,1) model and $R_t = (1 - \theta_1 - \theta_2)R + \theta_1 \psi_{t-1} + \theta_2 R_{t-1}$ is the conditional correlation matrix[3].

In addition, θ_1 and θ_2 are the non-negative parameters satisfying $(\theta_1 + \theta_2) < 1$, $R = \{\rho_{ij}\}$ is a time-invariant symmetric $N \times N$ positive definite parameter matrix with $\rho_{ii} = 1$ and ψ_{t-1} is the $N \times N$ correlation matrix of ε_τ for $\tau = t - M, t - M + 1, \ldots, t - 1$. The $i, j - th$ element of the matrix ψ_{t-1} is given as follows:

$$\psi_{ij,t-1} = \frac{\sum_{m=1}^{M} z_{i,t-m} z_{j,t-m}}{\sqrt{\left(\sum_{m=1}^{M} z_{i,t-m}^2\right)\left(\sum_{m=1}^{M} z_{j,t-m}^2\right)}}, \quad 1 \leq i \leq j \leq N \tag{10}$$

where$z_{it} = \varepsilon_{it}/\sqrt{h_{iit}}$ is the transformed foreign exchange rate returns residuals by their estimated standard deviations taken from the univariate AR(1)-FIAPARCH(1,d,1) model.
The matrix ψ_{t-1} could be expressed as follows:

$$\psi_{t-1} = B_{t-1}^{-1} L_{t-1} L_{t-1}' B_{t-1}^{-1} \tag{11}$$

whereB_{t-1} is a $N \times N$ diagonal matrix with $i - th$ diagonal element given by $\left(\sum_{m=1}^{M} z_{i,t-m}^2\right)$ and $L_{t-1} = (z_{t-1}, \ldots, z_{t-M})$ is a $N \times N$ matrix, with $z_t = (z_{1t}, \ldots, z_{Nt})'$.

To ensure the positivity of ψ_{t-1} and therefore of R_t, a necessary condition is that $M \leq N$. Then, R_t itself is a correlation matrix if $R_{t-1}$is also a correlation matrix. The correlation coefficient in a bivariate case is given as:

$$\rho_{12,t} = (1 - \theta_1 - \theta_2)\rho_{12} + \theta_2 \rho_{12,t} + \theta_1 \frac{\sum_{m=1}^{M} z_{1,t-m} z_{2,t-m}}{\sqrt{\left(\sum_{m=1}^{M} z_{1,t-m}^2\right)\left(\sum_{m=1}^{M} z_{2,t-m}^2\right)}} \tag{12}$$

[3]Engle (2002) derives a different form of DCC model. The evolution of the correlation in DCC is given by: $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha z_{t-1} + \beta Q_{t-1}$, where $Q = (q_{ijt})$ is the $N \times N$ time-varying covariance matrix of z_t, $\bar{Q} = E[z_t z_t']$ denotes the $n \times n$ unconditional variance matrix of z_t, while α and β are nonnegative parameters satisfying $(\alpha + \beta) < 1$. Since Q_t does not generally have units on the diagonal, the conditional correlation matrix R_t is derived by scaling Q_t as follows: $R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2}$.

Appendix 2

Table 1

Summary statistics and long memory test's results.

	INR/USD	SGD/USD	THB/USD	KRW/USD	PHP/USD	MYR/USD
Panel A: descriptive statistics						
Mean	9.70E-03	-0.0003	0.0048	5.30E-03	2.11E+00	0.0071
Maximum	3.9383	2.7618	20.769	13.645	0.2848	7.1957
Minimum	-3.756	-4.1444	-6.3532	-19.759	-0.4522	-9.1567
Std. Deviation	0.3747	0.3077	0.5437	0.7535	0.0245	0.4448
Skewness	0.4049***	-0.5101***	6.9982***	-1.0147***	-1.6854***	-0.7095***
	0.0000	0.0000	0.0000	0.0007	0.0000	0.0000
ExcessKurtosis	18.883***	17.955***	303.35***	134.71***	42.795***	82.396***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jarque-Bera	1.1280***	1.0212***	2.9117***	5.7314***	5.8184***	0.0214***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Panel B: Serial correlation and LM-ARCH tests						
$LB(20)$	104.515***	59.9159***	244.496***	337.159***	77.0265***	188.577***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$LB^2(20)$	1145.35***	1919.14***	238.099***	5153.42***	1180.13***	1939.33***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ARCH 1-10	57.054***	101.84***	7.7106***	201.34***	63.826***	96.340***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Panel C: Unit Root tests						
ADF test statistic	-52.6626*	-49.4786*	-51.7627*	-50.7144*	-52.1735*	-49.0296*
	-1.9409	-1.9409	-1.9409	-1.9409	-1.9409	-1.9409
Panel D: long memory tests (GPH test-d estimates)						
Squared returns						
$m = T^{0.5}$	0.3229*	0.3473*	0.2233**	0.1683**	0.2175*	0.3688*
	0.0751	0.0679	0.0398	0.039	0.065	0.0754
$m = T^{0.6}$	0.2671**	0.3706**	0.2085**	0.3675**	0.2302**	0.3904**
	0.0523	0.0381	0.0183	0.0264	0.0426	0.0447
Absolute returns						
$m = T^{0.5}$	0.3795*	0.5046*	0.5673*	0.3319*	0.3944*	0.4873*
	0.0662	0.0771	0.0684	0.0599	0.0866	0.0904
$m = T^{0.6}$	0.3624**	0.5115**	0.5783**	0.5970**	0.3380**	0.5314**
	0.0459	0.0451	0.044	0.0426	0.0491	0.0478

Notes: Exchange market returns are in daily frequency. $\boldsymbol{r^2}$and$|\boldsymbol{r}|$ are squared log return and absolute log return, respectively. $\boldsymbol{m}$ denotes the bandwith for the Geweke and Porter-Hudak's (1983) test. Observations for all series in the whole sample period are 7578. The numbers in brackets are t-statistics and numbers in parentheses are p-values. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively. $\boldsymbol{LB(20)}$and$\boldsymbol{LB^2(20)}$ are the 20th order Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, respectively.

Table 2

Univariate FIAPARCH(1,d,1) models (MLE).

	INR/USD		SGD/USD		THB/USD		KRWUSD		PHP/USD		MYR/USD	
	Coefficient	t-prob	Coefficient	t-prob	Coefficient	t-prob	Coefficient	t-prob	Coefficient	t-prob	Coefficient	t-prob
Estimate												
c	-0.0011*	0.0636	-0.0001*	0.0578	0.0006**	0.0302	0.0003**	0.0412	0.0002**	0.0301	-0.0002**	0.0493
ω	0.0001	0.3542	0.0102	0.4723	0.012	0.3214	0.0167	0.2315	0.0213	0.3604	0.0016	0.4785
d	0.9089***	0.0000	0.4677***	0.0000	0.8282***	0.0000	0.4693***	0.0000	0.4725***	0.0000	0.8982***	0.0000
ϕ	0.3830*	0.0857	0.4042*	0.0702	0.2951*	0.0504	0.4153**	0.0302	0.8204*	0.0702	-0.0118**	0.0107
β	0.9097***	0.0000	0.9620***	0.0000	0.9621***	0.0000	0.9339***	0.0000	0.8925***	0.0000	0.5416***	0.0002
γ	-0.2007**	0.0156	-0.2590**	0.0214	-0.0572**	0.0121	-0.4193**	0.0312	-0.1596*	0.0521	-0.0093**	0.0048
δ	2.0889***	0.0000	0.0377***	0.0000	0.1774***	0.0000	0.0368***	0.0000	1.0907***	0.0000	1.2423***	0.0008
v	2.3965***	0.0000	2.0845***	0.0000	2.2240***	0.0000	2.0182***	0.0000	2.0001***	0.0000	5.9534***	0.0000
Diagnostics												
$LB(20)$	63.124***	0.0000	250.723***	0.0000	104.00***	0.0000	946.61***	0.0000	1.7288	1.0000	1.9804	0.9957
$LB^2(20)$	4.3859	0.9995	608.866***	0.0000	31.1254	0.3625	775.96***	0.0000	0.0028	1.0000	0.0075	1.0000

Notes: For each of the six exchange rates, Table 2 reports the Maximum Likelihood Estimates (MLE) for the student-t-FIAPARCH(1,d,1) model. $\boldsymbol{LB(20)}$ and $\boldsymbol{LB^2(20)}$ indicate the Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, respectively. $\boldsymbol{v}$ denotes the the t-student degrees of freedom.parameter ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Appendix 3

Table 3

Estimation results from the bivariate FIAPARCH(1,d,1)-DCC model.

	INR/USD-SGD/USD		INR/USD-THB/USD		INR/USD-KRW/USD		INR/USD-PHP/USD	
	coefficient	t-prob	coefficient	t-prob	coefficient	t-prob	coefficient	t-prob
Panel A: Estimates of Multivariate DCC								
a	0.0033***	0.0006	0.0046***	0.0000	0.0022***	0.0028	0.0054***	0.0039
b	0.9958***	0.0000	0.9931***	0.0000	0.9972***	0.0000	0.9884***	0.0000
v	2.3582***	0.0000	2.2910***	0.0000	2.3065***	0.0000	2.2294***	0.0000
Panel B : Diagnostic tests								
$Hosking(20)$	179.063***	0.0000	197.231***	0.0000	190.415***	0.0000	167.674***	0.0000
$Hosking^2(20)$	38.1371	0.3714	91.1405	0.1466	46.8908	0.1527	26.5222	1.0000
$Li-McLeod(20)$	178.976***	0.0000	197.108***	0.0000	129.821***	0.0000	167.602***	0.0000
$Li-McLeod^2(20)$	38.1303	0.3722	91.1204	0.1469	46.8794	0.1529	26.5994	1.0000

Notes: The superscripts ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively.$\boldsymbol{v}$indicates the student's distribution's degrees of freedom. $\boldsymbol{Hosking\ (20)}and\boldsymbol{Hosking^2(20)}$ denote the Hosking's Multivariate Portmanteau Statistics on both standardized and squared standardized Residuals. $\boldsymbol{Li-McLeod\ (20)}$ and $\boldsymbol{Li-McLeod^2(20)}$ indicate the Li and McLeod's Multivariate Portmanteau Statistics on both Standardized and squared standardized Residuals.

Table 4

Estimation results from the bivariate FIAPARCH(1,d,1)-DCC model (continued).

	SGD/USD-THB/USD		SGD/USD-KRW/USD		SGD/USD-PHP/USD		THB/USD-KRW/USD	
	coefficient	t-prob	coefficient	t-prob	coefficient	t-prob	coefficient	t-prob
Panel A: Estimates of Multivariate DCC								
a	0.0120***	0.0001	0.0109***	0.0000	0.0036**	0.0101	0.0062***	0.0008
b	0.9760***	0.0000	0.9870***	0.0000	0.9945***	0.0000	0.9897***	0.0000
v	2.3721***	0.0000	2.4025***	0.0000	2.3099***	0.0000	2.3386***	0.0000
Panel B : Diagnostic tests								
$Hosking(20)$	147.568***	0.0000	219.719***	0.0000	117.678***	0.0031	177.814***	0.0000
$Hosking^2(20)$	218.297***	0.0000	85.1280	0.3602	31.2288	0.2708	25.2348	0.1185
$Li-McLeod(20)$	147.498***	0.0000	219.670***	0.0000	117.684***	0.0031	177.758***	0.0000
$Li-McLeod^2(20)$	218.124***	0.0000	85.1781	0.3714	31.2251	0.2710	25.23	0.1187

Notes: The superscripts ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively.$\boldsymbol{v}$indicates the student's distribution's degrees of freedom. $\boldsymbol{Hosking\ (20)}and\boldsymbol{Hosking^2(20)}$ denote the Hosking's Multivariate Portmanteau Statistics on both standardized and squared standardized Residuals. $\boldsymbol{Li-McLeod\ (20)}and\boldsymbol{Li-McLeod^2(20)}$ indicate the Li and McLeod's Multivariate Portmanteau Statistics on both Standardized and squared standardized Residuals.

Table 5

Estimation results from the bivariate FIAPARCH(1,d,1)-DCC model (continued).

	INR/USD-MYR/USD		SGD/USD-MYR/USD		THB/USD-MYR/USD		KRW/USD-MYR/USD	
	coefficient	t-prob	coefficient	t-prob	coefficient	t-prob	coefficient	t-prob
Panel A: Estimates of Multivariate DCC								
a	0.0080***	0.0001	0.0165***	0.0000	0.0172***	0.0000	0.0085***	0.0079
b	0.9907***	0.0000	0.9780***	0.0000	0.9827***	0.0000	0.9895***	0.0000
v	2.1625***	0.0000	2.2427***	0.0000	2.2214***	0.0000	2.2084***	0.0000
Panel B : Diagnostic tests								
$Hosking(20)$	206.508***	0.0000	281.362***	0.0000	179.553***	0.0000	110.579**	0.0133
$Hosking^2(20)$	55.8978	0.9723	690.407***	0.0000	111.689***	0.0074	91.9801	0.1332
$Li-McLeod(20)$	206.433***	0.0000	281.322***	0.0000	179.492***	0.0000	110.566**	0.0134
$Li-McLeod^2(20)$	55.9878	0.9717	690.261***	0.0000	111.716***	0.0073	91.941	0.1338

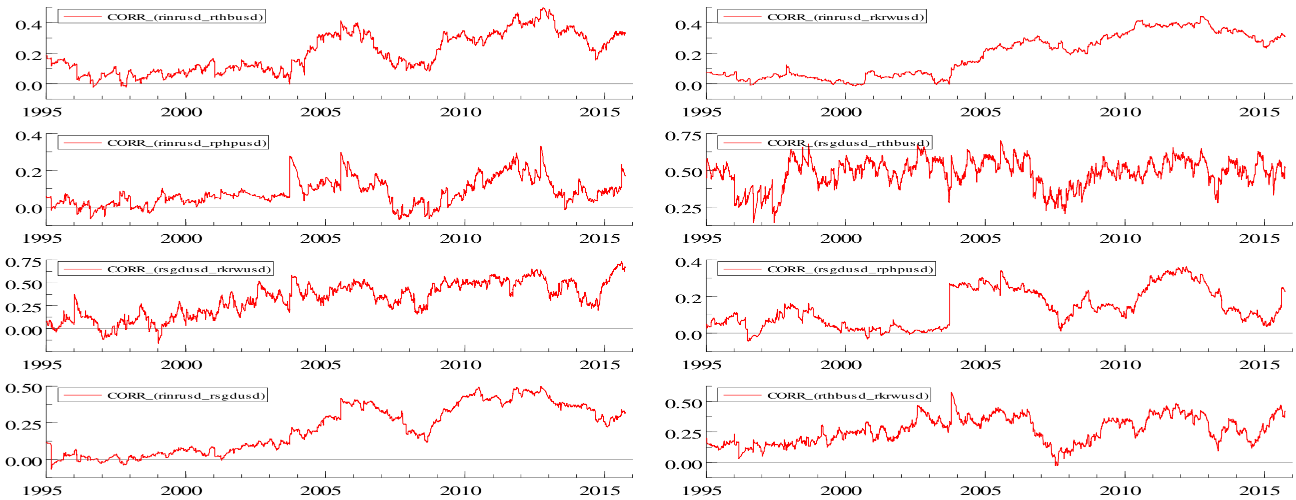
Notes: The superscripts ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively.$\boldsymbol{v}$indicates the student's distribution's degrees of freedom. $\boldsymbol{Hosking\ (20)}and\boldsymbol{Hosking^2(20)}$ denote the Hosking's Multivariate Portmanteau Statistics on both standardized and squared standardized Residuals. $\boldsymbol{Li-McLeod\ (20)}and\boldsymbol{Li-McLeod^2(20)}$ indicate the Li and McLeod's Multivariate Portmanteau Statistics on both Standardized and squared standardized Residuals.

Table 6
Estimation results from the bivariate FIAPARCH(1,d,1)-DCC model (continued).

	THB/USD-PHP/USD		KRW/USD-PHP/USD	
	coefficient	t-prob	coefficient	t-prob
Panel A: Estimates of Multivariate DCC				
a	0.0053***	0.0002	0.0032***	0.0000
b	0.9888***	0.0000	0.9960***	0.0000
v	2.2601***	0.0000	2.2690***	0.0000
Panel B : Diagnostic tests				
$Hosking(20)$	151.736***	0.0000	120.274***	0.0019
$Hosking^2(20)$	82.8074	0.3334	68.4856	0.7707
$Li - McLeod(20)$	151.675***	0.0000	120.264***	0.0019
$Li - McLeod^2(20)$	82.8023	0.3335	68.4994	0.7703

Notes: The superscripts ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively. $\boldsymbol{v}$ indicates the student's distribution's degrees of freedom. $\boldsymbol{Hosking}$ $(\mathbf{20})$and$\boldsymbol{Hosking^2}(\mathbf{20})$ denote the Hosking's Multivariate Portmanteau Statistics on both standardized and squared standardized Residuals. $\boldsymbol{Li - McLeod}$ $(\mathbf{20})$ and $\boldsymbol{Li - McLeod^2}(\mathbf{20})$ indicate the Li and McLeod's Multivariate Portmanteau Statistics on both Standardized and squared standardized Residuals.

Appendix 4



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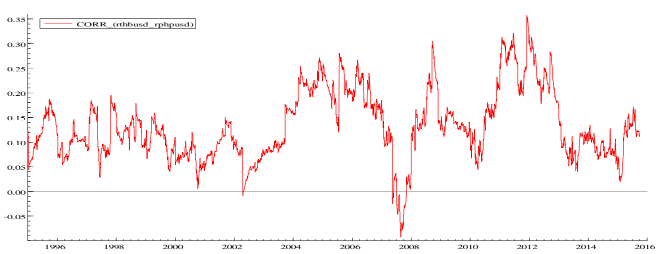

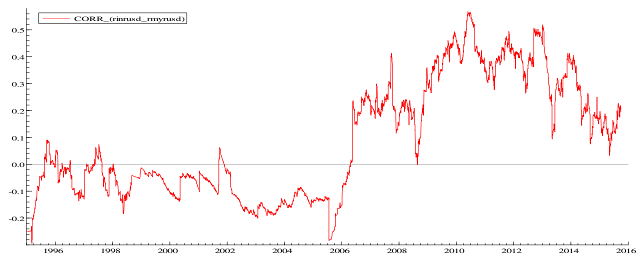

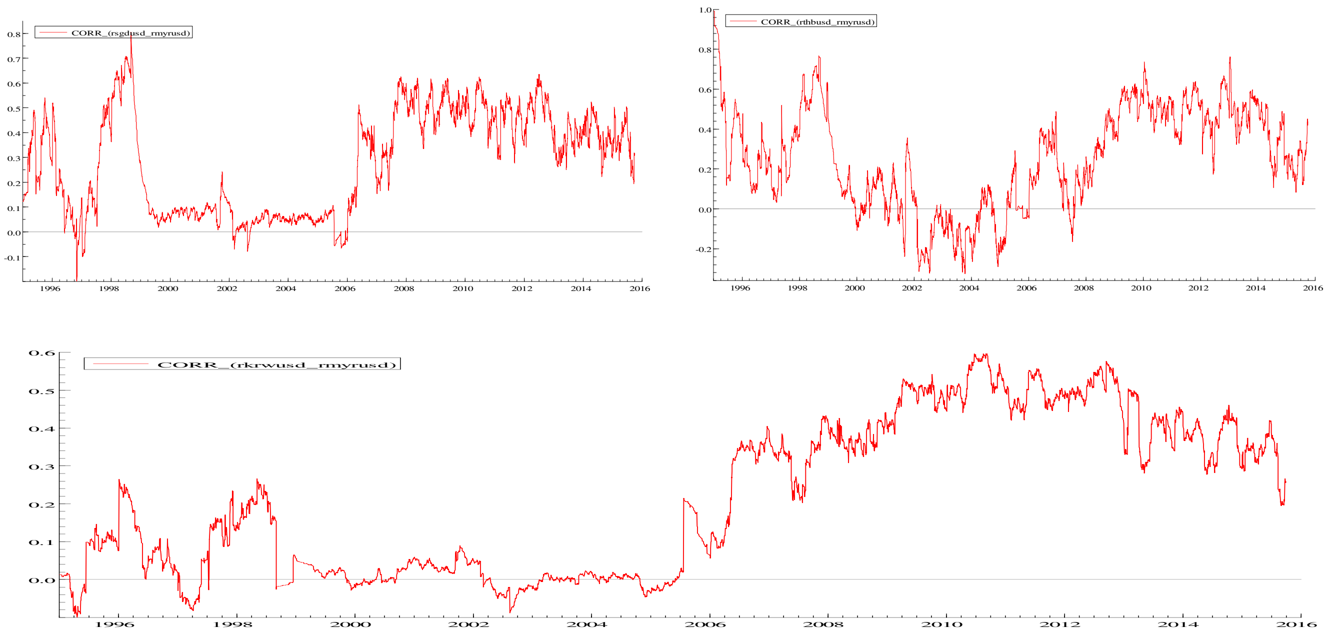

Fig.1. The DCC behavior over time.