Detecting exchange rate contagion in Asian exchange rate markets using asymmetric DDC-GARCH and R-vine copulas

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Abstract

This study uses asymmetric DCC-GARCH models and copula functions for studying exchange rate contagion in a group of twelve Asia-Pacific countries. Using daily data between November 1991 and March 2017, shows that extreme market movements are mainly associated with the high degree of interdependence registered by countries in this region. The evidence of contagion is scarce. Asymmetries do not appear to be important. Specifically, currency co-movements are statistically identical during times of extreme market appreciation and depreciation, indicating that phenomena such as the fear of "appreciation" do not appear to be relevant in the region's foreign exchange markets.

Keywords: Exchange rate contagion; Asian financial crisis; Copula functions; DCC-GARCH models.

JEL Classification: C32; C51; E42.

1. Introduction

This paper studies exchange rate contagion in Asia-Pacific markets between 1991 and 2017 following an R-vine copula approach.[3] As in

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3 We use R-vines in our study for two main reasons. The first is that most related studies using copula functions follow a vine approach. Hence, in order to make our results more comparable to those of the closest papers in the literature, we maintain their econometric approach. Second, the most general vines are regular vines. C-vines and D-vines are particular cases of R-vines. A few recent papers in this strand of the literature have used dynamic copulas (with and without regime switching, nonparametric approaches, and wavelet coherence analysis. An interesting extension of our study would be to use these

Forbes & Rigobon (2001), contagion consists of a significant increase in cross-market linkages after the occurrence of a shock in a country's financial market. Defining contagion this way offers two important advantages. First, it allows distinguishing between temporal and permanent mechanisms for the transmission of crises, facilitating the implementation of macro-prudential policies. Second, it provides a useful framework for empirically testing contagion in a very general setup. We use here the tail dependence criterion proposed by Cherubini, Luciano, & Vecchiato (2004), used in related studies including Czado, Schepsmeier, & Min (2012), Loaiza-Maya, Gomez- Gonzalez, & Melo-Velandia (2015a,b) and Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia (2019).

Contagion during currency crisis has been extensively studied. Much of the ample empirical literature emphasizes on its geographical component (see S. B. Lee & Kim, 1993; Forbes & Rigobon, 2001; Dungey, Fry, González- Hermosillo, & Martin, 2006; Lucey & Voronkova, 2008; Arouri, Bellalah, Hamida, & Nguyen, 2012). Currency crises tend to be regional, as they affect countries in geographical proximity Glick & Rose (1999); De Gregorio & Valdes (2001); Beirne & Gieck (2014); Grabowski & Welfe (2016); Y. Lee, Hong, & Yang (2016).

Studying developed and Asia-Pacific exchange rate markets from the 1990s on is interesting for various reasons. First, the term "contagion" in financial markets began to be used after the Asian banking and currency crises of 1997 (Claessens & Forbes, 2001). There is relative consensus in the literature that these are benchmark events for studies on interdependence and spillovers among financial markets. Hence, providing further evidence for a better understanding of contagion during those episodes is always useful. Second, the Asian-Pacific region's importance in the global economy

is growing. Estimates of the IMF indicate that, by 2030, Asia's economy will be larger than that of the United States and the European Union combined. Countries in this region are also gaining increasing importance in international financial markets and, therefore, their potential of transmitting volatility shocks to other emerging and developed economies (R. F. Engle, Gallo, & Velucchi, 2012). Finally, currency markets in the region have undergone important reforms and transformations over the last two decades. Thus, data presents sufficient heterogeneity for identifying interdependence and contagion appropriately.

other approaches in the context of exchange rate co-movements in Asia.

Results show that Malaysia ringgit is central in the region's exchange rate network. On the contrary, Japan yen and New Zealand dollar are the least integrated currencies in the network. Contrasting with recent studies that have encountered evidence of contagion in Latin American and East European countries, this paper shows that little evidence of contagion is encountered for the Asia-Pacific region. Exchange rate co-movements are mainly due to high interdependence between countries, as in Forbes & Rigobon (2001).

We find that exchange rate dependencies in Asia behave quite similarly during periods of large appreciation and depreciation. In other words, our evidence suggests that Asian the asymmetries in exchange rate contagion that have been encountered for other regions and other samples of countries (see, for instance, (Levy-Yeyati, Sturzenegger, & Gluzmann, 2013)) do not hold for our sample of Asian economies. This result may obey to the fact that central bank intervention is more symmetric in Asian countries than, for instance, in Latin American countries in which a "fear of appreciation" effect has been identified in the literature.

We contribute to the literature on exchange rate contagion by showing, using a large number of Asian economies and a long sample period covering the global financial crisis, that exchange rate co-movements in this region are mainly due to the fact that their foreign exchange rate markets are being more integrated. This result contrasts importantly with those of other similar papers that have shown evidence of contagion in other regions of the world, such as Latin America (Loaiza-Maya, Gomez-Gonzalez, & Melo-Velandia (2015a,b)). Our results go in line with those of Forbes & Rigobon (2001), who show that during the Asian financial crisis of 1997 exchange rate interdependence increased for countries in the region, without evidence of contagion. Additionally, our asymmetric DCC GARCH approach allows us to test for possible asymmetric co-movements during large appreciations and depreciations. Results indicate that co-movements are symmetric in this sense. This result, which contrasts with those of studies for other regions as well, points out that contagion exhibits an important regional component.

The fact that contagion has an important regional component provides important results for global investors. Specifically, it indicates that global hedging strategies require regional diversification. This finding complements those of Dimitriou & Kenourgios (2013) and Dimitriou et al. (2017) who show that correlation dynamics between currencies vary largely over time, increasing vulnerabilities during times of financial distress. Hence, there are higher portfolio diversification benefits during times of financial distress, since holding a diversified currency portfolio reduces systemic risk more during those times.

This paper is organized as follows. Section 2 is a data section. Descriptive statistics are presented. Section 3 introduces the ARIMA-GARCH best models and the DCC specification to account for asymmetric effects to obtain the standardized residuals. The Sklar's theorem is presented in Section 4 along with R-vine and tail dependence definitions which are used in Section 5 for empirical estimations. The last section concludes.

2. Data and descriptive statistics

This document covers a synchronized period from 7/Nov/1991 to 16/Mar/2017 for daily closing values obtained from Bloomberg L.P. Exchange rate data is gathered for the twelve Asia-Pacific economies: Australia (AUD), Hong Kong (HKD), India (INR), Indonesia (IDR), Japan (JPY), Malaysia (MYR), New Zealand (NZD), Singapore (SGD), South Korea (KRW), Thailand (THB), Taiwan (TWD) and The Philippines (PHP). Nominal exchange rates are depicted in Figure 2.

Some recent papers argue that results from hypothesis tests in finance are frequency dependent (Narayan & Sharma, 2015; and, Narayan et al., 2015). Therefore, the selection of the frequency of the data is not trivial in empirical studies in finance. Daily data has shown to contain richer information than data in lower frequencies (see Kenourgios et al., 2016; Bannigidadmath & Narayan, 2016).

Table 1 presents descriptive statistics for exchange rate returns.[4] Notice that means are positive and negative indicating devaluations and appreciations over the period of study. Return distribution are skewed, presenting higher mass on right tails as well as left tails. This fact illustrates that currencies are affected by depreciations and appreciations. However, it appears to be the case that appreciations are more frequent within individual countries' exchange rates and justify the exploration of asymmetries in interdependence and contagion.

Interestingly, excess Kurtosis are positive in all cases. The distribution exhibit platykurtic distributions, having fewer extreme values. This

4 We report information on returns rather than on exchange rates, as the former are covariance stationary while the latter don't. Returns are computed as the logarithmic difference of nominal ex-change rates.

$$r_{i,t} = \ln(Y_{i,t}) - \ln(Y_{i,t-1}), (1)$$

All exchange rates are computed as the number of units of each country's currency that buy one US dollar.

empirical fact indicates that most countries in the Asia-Pacific region exhibit few episodes of high exchange rate volatility, possibly associated with active central bank exchange rate intervention policies. However, considerable heterogeneity is observed between countries.

Jarque-Bera test results provide evidence for rejecting the normal distribution hypothesis in all countries at conventional confidence levels. Additionally, D-values for Kolmogorov-Smirnov statistics are positive, providing further evidence that returns are not normally distributed. This evidence together suggests the importance of exploring alternative distributions that can better represents exchange rate returns and their dependence structures.

Table 1

Exchange rates returns. Descriptive Statistics.

	AUD	**HKD**	**INR**	**IDR**	**JPY**	**MYR**	**NZD**	**SGD**	**KRW**	**THB**	**TWD**	**PHP**
Mean.	-3.15e-06	1.18e-08	-0.0001	-0.0002	2.07e-05	7.32e-05	3.34e-05	2.70e-05	-6.08e-05	-4.76e-05	-2.35e-05	-9.81e-05
Median.	0.0002	0.00	0.00	0.00	0.00	0.00	0.0001	0.00	0.00	0.00	0.00	0.00
Maximum.	0.0827	0.0062	0.0347	0.2309	0.0705	0.0985	0.0451	0.0371	0.2034	0.0855	0.0323	0.0644
Minimum.	-0.0729	-0.0028	-0.0610	-0.1999	-0.0547	-0.0770	-0.0673	-0.0302	-0.1525	-0.1779	-0.0333	-0.1085
Std.Dev.	0.0075	0.0003	0.0041	0.0135	0.0068	0.0050	0.0075	0.0035	0.0086	0.0059	0.0029	0.0061
Skewness.	-0.2555	0.9591	-1.2494	-0.7468	0.3594	0.4196	-0.2234	0.1825	-0.2602	-3.9070	-0.3543	-1.1868
Kurtosis.	12.543	29.377	24.502	84.303	8.5256	76.403	6.5774	12.061	104.41	154.53	18.458	39.589
Jarque-Bera.	25086.5	192121.2	128704.5	1816225.	8528.2	1480114.	3570.1	22588.7	2824798	6323502.	65777.1	369271.9
Probability.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kolmogorov-Smirnov.	0.06	0.22	0.14	0.23	0.06	0.19	0.05	0.07	0.17	0.17	0.11	0.14
Probability.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

3. ARIMA-GARCH

The best fit ARIMA models are calculated according to (BIC and AIC) for each currency, as shown in Table 2. The standard GARCH specification is applied:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 . (2)$$

Using a Student-t conditional distribution as proposed by Hansen (1994):

$$g(z \vee \eta, \lambda) = \begin{cases} bc\left(1 + \frac{1}{\eta-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-(\eta+1)/2} & z < -a/b, \\ bc\left(1 + \frac{1}{\eta-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-(\eta+1)/2} & z \geq -a/b, \end{cases} (3)$$

Where $2 < \eta < \infty$, and $-1 < \lambda < 1$. The constants a, b, and c are given by

$$a = 4\lambda c\left(\frac{\eta-2}{\eta-1}\right), b^2 = 1 + 3\lambda^2 - a^2 \quad \text{and} \quad c = \frac{\Gamma\left(\frac{\eta+1}{2}\right)}{\sqrt{\pi(\eta-2)}\,\Gamma\left(\frac{\eta}{2}\right)} .$$

Table 2
Best fit ARIMA models.

Country	ARIMA	AIC	BIC
Australia	(1,1,1)	-49368.54	-49348.16
Hong Kong	(1,1,1)	-113245.4	-113225.1
India	(0,1,2) with drift	-102750.9	-102723.7
Indonesia	(1,2,1)	-64371.53	-64351.15
Japan	(0,1,0)	-108383.1	-108376.2
Malaysia	(4,1,4)	-67904.48	-67843.34
New Zealand	(0,1,0)	-51445.11	-51438.31
Singapore	(0,1,3)	-60926.94	-60899.77
South Korea	(0,1,0)	-77876.19	-77869.4
Thailand	(1,1,1)	-95429.72	-95409.34
Taiwan	(0,1,0)	-103372.6	-103365.8
The Philippines	(1,1,1) with drift	-94573.04	94545.87

DCC

Tse & Tsui (2000) and R. Engle (2002) introduced the dynamic conditional correlations (DCC) as an extension to the CCC model of Bollerslev (1990), to correct for constant correlation over time. The variance-covariance matrix is defined as:

$$H_t = D_t R_t D_t, (4)$$

Where $D_t = diag\sqrt{h_{i,j}}$. D_t is a diagonal matrix containing the conditional standard deviations on the leading diagonal; R_t is the conditional correlation matrix, its specification is formulated by R. Engle

(2002) as $R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}$. Q comes from a general MGARCH model where more complex positive definite multivariate GARCH models could be used for the correlation parametrizations.

$$Q = S \circ (u' - A - B) + A \circ \varepsilon_{t-1} \varepsilon'_{t-1} + B \circ Q_{t-1} (5)$$

Where $\circ$ is the Hadamard product; $A, B \wedge (u' - A - B)$ are positive semidefinite and Q will be positive semidefinite.

Chiang, Jeon, & Li (2007) implemented a symmetric DCC-GARCH to eight daily Asian stock-return data series from 1990-2003. The DCC-GARCH specification in this document accounts for asymmetric effects as recommended by (Cappiello, Engle, & Sheppard, 2006), i.e. volatility increases more after a negative shock than after a positive shock of the same magnitude. This model is appropriate for measuring time-varying conditional correlations and the responses to news and innovations. The standard residual for our model to each currency are displayed in figure 3.

The pseudo-sample associated with these residuals to uniform margins $(u_1, u_2 \in [0,1])$ can be used to construct currency-pairs as presented in figure 4. In this matrix the lower half bellow the diagonal presents the level plots or contours and the half above indicates the Kendall's taus measure of all possible pairs. These uniform margins are used for analyzing their joint distribution and ultimately their dependence structure.

4. Sklar's theorem, 1959

Copula functions are useful for modelling multivariate dependence, especially when normality fails to be a good assumption for distributions, as in our case. Moreover, Copulas facilitate isolating dependence between random variables from their marginal distributions.

Since the probability integral transform is invertible, the copula also describes the dependence between the original variables. Notably in economics there is often more information about marginal distributions of related variables than their joint distribution. Inasmuch as copulas can capture dependence structure regardless of the form of the margins, a copula approach is likely very useful in econometrics.

Succinctly, let a *n*-dimensional distribution function H be decompose into two parts, the marginal distribution functions F_i and the copila C. Let

H be a joint distribution function with margins F_i . Then there exists a copula C such that for all x_i in $\acute{R}^n$ following the seminal work of Sklar (1959),

$$H(x_1 \ldots x_n) = C(F_1(x_1), \ldots, F_n(x_n)).(6)$$

Let $F_1, \ldots, F_n$ be the distribution functions. If $F_1, \ldots, F_n$ are all continuous, then C is unique; otherwise, C is uniquely determined on $RanF_1 x \ldots Ran F_n$. Conversely, if C is a *n*-copula and $F_1, \ldots, F_n$ are distribution functions, then the function H defined above is a *n* distribution function with margins $F_1, \ldots, F_n$ (see Joe, 1997; Nelsen, 2007).

R-vine

A flexible graphical method proposed by various authors Joe (1996); Bedford & Cooke (2001, 2002); Kurowicka & Cooke (2006) describes multivariate copulas as dependency model for the distribution of certain pairs of variables conditional on a specified set of variables. Using this cascade of bivariate copulas, so called pair-copulas construction (PCC); the recognition of the needed pairs of variables and their set of conditional variables is facilitated by an array of trees.

Vines arrange the n(n − 1)/2 pair-copulas of a n-dimensional PCC in n − 1 linked trees. In general, the structure captures conditional dependencies in higher trees and the order of the nodes are selected in such a way that the strongest pairwise dependencies are capture in the first tree.

The specification of the R-vine copula has the following arguments: (**F** $, v, B ¿$ is an R-vine copula specification if **F** $¿(F_1, \ldots, F_n)$ is a vector of continuous invertible distribution functions, as Sklar’s Theorem illustrated in equation 6, v is an *n*-dimensional R-vine and $B = \{B_e \vee i = 1, \ldots, n-1; e \in E_i\}$ is a set of copulas with B_e being a bivariate copula $(X_{C_{e,a}}, X_{C_{e,b}})$.

The R-vine decomposition of a multivariate density is:

$$\prod_{e\in E_i} c_{C_{e,a},C_{e,b}\vee D_e}(¿F_{C_{e,a}\vee D_e}(x_{C_{e,a}}\vee x_{1_{De}},\ldots,x_{n_{De}}),F_{C_{e,b}\vee D_e}(x_{C_{e,b}}\vee x_{1_{De}},\ldots,x_{n_{De}})),(7)$$

$$f(x_1,\ldots,x_n)=\prod_{k=1}^{n} f_k(x_k)\times\prod_{i=1}^{n-1}¿$$

where f_k are the marginal densities $k=1,\ldots,n, c_{C_{e,a},C_{e,b}\vee D_e}$ is the copula density of B_e for edge $e=\{a,b\}$ and $x_{i_{D,e}}\in D_e$ for $i=1,\ldots,n$. Joe (1996) describes the strategy to obtain the conditional distribution $F_{C_{e,a}\vee D_e}(x_{C_{e,a}}\vee\cdot)$ and $F_{C_{e,b}\vee D_e}(x_{C_{e,b}}\vee\cdot)$.

Tail dependence

The concept of tail dependence is used as an advanced device to identify contagion among currencies when extreme values occur. This measure is only copula based and can thus be used in the parametrization of copulas. Joe (1997) defines this as the amount of dependence in the upper-quadrant tail or lower-quadrant tail of a bivariate distribution.

By definition:

$$\lim ¿_{u\searrow 0}\frac{C(u,u)}{u}(8)$$
$$\lambda_L=¿$$

And

$$\lim ¿_{u\nearrow 1}\frac{1-2u+C(u,u)}{1-u}(9)$$
$$\lambda_U=¿$$

Where λ_L is the lower tail and λ_U is the upper tail dependence for given bivariate copula family and parameter(s).

A copula is said to have a lower (upper) tail dependence if $\lambda_L\neq 0(\lambda_U\neq 0)$.

The lower tail dependence measure $\lambda(¿¿L)¿$ is the limiting value of $\frac{C(u,u)}{u}$, which is the conditional probability

$Pr[U_1<u \vee U_2<u](¿Pr[U_2<u \vee U_1<u])$ and the upper tail dependence $\overset{\lambda}{\underset{¿}{(¿¿U)}}$ is the conditional probability $Pr[U_1>u \vee U_2>u](¿Pr[U_2>u \vee U_1>u])$.

5. Estimation

This document uses the automated strategy of jointly searching the appropriate R-vine tree structure, the pair copula families and their parameter values, formulated Dissmann, Brechmann, Czado, & Kurowicka (2013). Succintly, the method consists in selecting exchange rate pairs, finding the best bivariate copula families for each pair using information criteria, and estimating the corresponding parameters by Maximum Likelihood.

Table 5 presents estimation results. The first column displays the tree number. The edge, shown in the second column, presents pair-currencies (unconditional for the first tree while conditional for the rest of them). The best type of copula fit are presented in the third and fourth columns. The other three columns show information on the value of parameters and Kendall's Tau. Note that a t distribution is frequently the most adequate for the different exchange rate pairs. Other distributions that frequently appear as adequate belong to the SBB family.

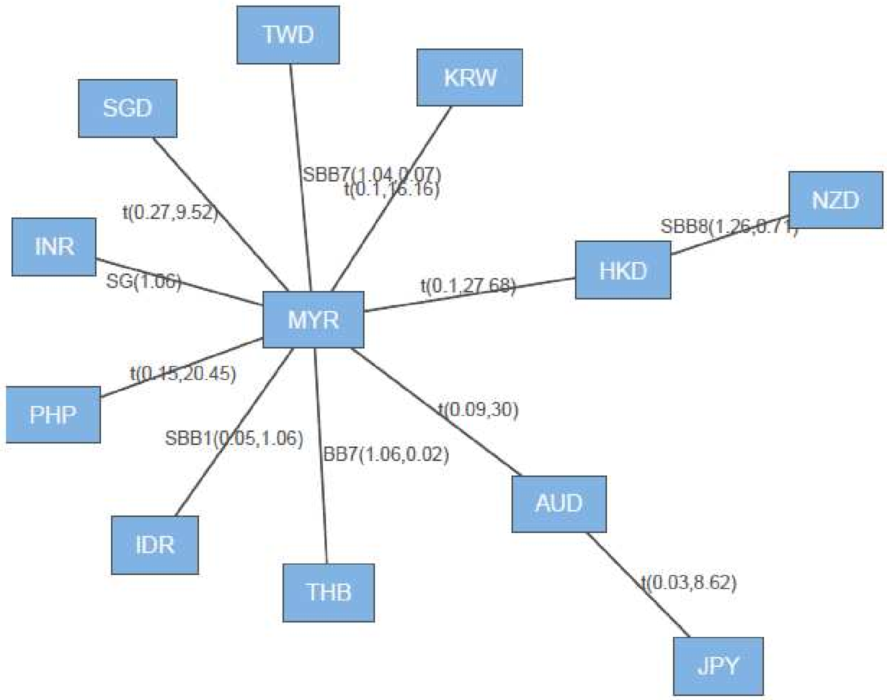
The Malaysia ringgit maximizes the sum of the absolute empirical Kendall's Tau (see figure 4).

$$max \sum_{e=[j,k]\in spanning\,tree\,\hat{\tau}_{j,k}} \square (10)$$

In other words, the first spanning tree (figure 1) presents Malaysia's ringgit as the main node while the rest of the currencies are its immediate edges (except for Japan's yen and New Zealand's dollar). These two currencies are connected to the network through other currencies. In the case of the Yen, its connection its mediated by the Australian Dollar. Meanwhile, New Zealand's Dollar is connected through Hong Kong's currency.

These are interesting results. They are useful for investors, as they highlight important issues regarding diversification opportunities. Specifically, we show that Malaysia is the main shock transmitter. However, volatility transmission flows first to most countries of the Asia-Pacific region, including Australia and Hong Kong, while Japan and New Zealand are only indirectly affected by their connection to other countries in the network.

Figure 1. Tree 1 in R-vine.



Since we want to identify contagion among currencies when extreme values occur, the tails values are calculated using definitions 8 and 9. The upper tail dependence of the twelve Asian exchange rates are displayed on the top right panel of table 3. Upper tail dependence is associated with currencies co-movement for large depreciations. On the other hand, lower tail dependence indicates large appreciations as shown on the bottom panel in the same table.

Table 3 shows our main results regarding tail dependence. Notice that tail values are mainly symmetric and their probabilities are lower than 1% (however, different from zero in most cases). The fact that values are symmetric for most pairs implies that interdependence is similar in times of extreme currency appreciations and depreciations with respect to the US Dollar. This result, that contrasts with those of the majority of studies (see Loaiza-Maya, Gomez-Gonzalez, & Melo-Velandia, 2015a,b), shows that phenomena such as the “fear of appreciation” (see Levy-Yeyati, Sturzenegger, & Gluzmann, 2013) are not present in the Asia-Pacific region. In other words, while central banks in these countries conduct exchange rate intervention, it appears that their interventions do not depend on whether the exchange rate is devaluating or revaluating. In this sense, the “fear of appreciation” seems to be a common phenomenon mostly in Latin American and East European economies.

Table 3
Tail Dependence.

	AUD	HKD	INR	IDR	JPY	MYR	NZD	SGD	KRW	THB	TWD	PHP
AUD		2.70e-10	0.00	0.00	2.15e-3	0.00	5.14e-6	1.01e-2	4.77e-6	0.00	2.69e-4	1.35e-2
HKD	0.00		0.00	3.67e-6	9.32e-5	0.00	0.00	0.00	1.73e-2	6.63e-4	1.56e-3	7.29e-2
INR	0.00	0.00		9.18e-6	0.00	1.27e-4	0.00	0.00	6.39e-6	3.75e-5	0.00	6.40e-4
IDR	0.00	3.67e-6	9.18e-6		0.00	3.54e-6	3.65e-6	4.93e-5	0.00	1.40e-3	0.00	0.00
JPY	2.15e-3	9.32e-5	4.19e-2	0.00		0.00	8.08e-6	0.00	1.97e-3	0.00	0.00	1.77e-5
MYR	0.00	0.00	1.27e-4	3.54e-6	0.00		0.00	0.00	0.00	2.57e-5	6.91e-8	0.00
NZD	5.14e-6	0.00	0.00	3.65e-6	8.08e-6	0.00		1.12e-2	1.35e-5	0.00	3.88e-2	4.25e-5
SGD	1.01e-2	1.16e-2	0.00	4.93e-5	0.00	0.00	0.00		5.60e-6	7.09e-4	1.16e-4	6.07e-7
KRW	4.77e-6	0.00	6.39e-6	2.91e-14	1.97e-3	0.00	1.35e-5	5.60e-6		0.0075	0.0003	0.0015
THB	0.00	6.63e-4	3.75e-5	1.40e-3	0.00	2.57e-5	1.88e-2	7.09e-4	0.0075		0.0011	0.0321***
TWD	2.69e-4	1.56e-3	0.00	0.00	0.00	0.00	5.34e-7	1.16e-4	0.0003	0.0011		5.92e-5
PHP	1.35e-2	3.33e-14	6.40e-4	0.00	1.77e-5	7.77e-2	4.25e-5	7.52e-2	0.0015	0.0321	0.0507**	

***if λ_L or $\lambda_U \geq$ Pr[1%]; **if λ_L or $\lambda_U \geq$ Pr[5%].

Pair-currencies with both tails equal to zero. $(\lambda_L = 0 \wedge \lambda_U = 0)$ as in Gaussian copulas are: Australian dollar- (Indian rupee, Indonesian rupiah, Malaysia ringgit, Thailand baht), Hong Kong dollar-(Indian rupee, Malaysia ringgit, New Zealand dollar), Indian rupee-(New Zealand dollar, Singapore dollar, Taiwan new dollar), Indonesia rupiah- (Japan yen, Taiwan new dollar, Philippine peso), Japan yen-(Malaysia ringgit, Singapore dollar, Thailand baht, Taiwan new dollar) and Malaysia ringgit-(New Zealand dollar, Singapore dollar, South Korea won). In other words, for these cases there is not contagion from large appreciations or depreciations.

This finding then encourages the same results as Forbes & Rigobon (2001); Basu (2002); Bordo & Murshid (2000). In other words, transmission mechanisms are fairly stable among these currencies and that little contagion can be spread. One interpretation is that the Asian financial crisis of 1997- 1998 made necessary to implement various types of policy coordination which main purpose was to internalize the externalities and spill-over effects that arise from economic regionalism. Moreover, there was a growing resentment toward the International Monetary Fund (IMF) and U.S. handling of the crisis that intensified the interest in the East Asian Economic Group (EAEG), which took the form of the ASEAN Plus Three (APT) framework.

Central banks and governments in East Asia agreed to create a regional self-help mechanism for effective prevention and management of financial crises which included regional economic surveillance led by the Economic Review and Policy Dialogue (ERPD), a regional liquidity support facility, called the Chiang Mai Initiative (CMI), and local-currency bond market development. Kawai (2005) suggests that the lesson from the Asian financial crisis was a clear need for effective prevention, management and resolution of financial crises and contagion. A thought that seems to justify the tail dependence values in upper and lower cases equal to zero.

The Philippine peso-Taiwan new dollar has only a lower tail or appreciation probability greater than 5%. The ASEAN currencies Philippine peso-Thailand baht have symmetric upper and lower tails greater than 1%.

Results for tests on standardized residuals indicate that our empirical specifications are adequate. See Table 4.

Table 4

Multivariate Specification tests for the standardized residuals

	Null Hypothesis	**Lags**	**Statistics**	**P-Value**
Portmanteau	No autocorrelation	300	24795.691	0.215
LM (square residuals)	No MGARCH effect	100	94545.87	0.242

We perform two types of robustness tests. One deals with country exclusion and the other with the reduction of the sample period. Regarding the first, we excluded constructed R-vines excluding the countries with the less developed foreign exchange markets in our sample and observed that results were qualitatively identical. Particularly, no evidence of contagion was encountered. Regarding the second, the sample period was shortened to exclude the recent recent international financial crisis. Data was considered only for the period between 2009 and 2018. Results were qualitatively identical as well.

6. Conclusions

This paper studies Exchange rate contagion in the Asia-Pacific region. Using daily data spanning the period November 1991 to March 2017, together with DCC-GARCH models and copula functions, the paper explores the behavior of interdependence in times of extreme market appreciations and depreciations and their potential asymmetric effects.

In this context, contagion is considered as a situation in which exchange rate cross-market linkages significantly increase after the occurrence of a shock in a country's financial market. The sample contains countries from a unique region as evidence shows that currency crises tend to be regional, i.e., they affect countries in geographical proximity.

The R-vine copula approach followed in this study allows the identification of the best bivariate copula family for each exchange rate pair, as permits the estimation of tail dependence coefficients for extreme exchange rate appreciations and depreciations. Results show that, in most cases, a t-copula or a copula pertaining to the SBB family are the best fit. Network centrality of Malaysia ringgit is identified, while the Japan yen and the New Zealand dollar are the most isolated currencies from the sample. These results provide important information for investors interested in portfolio balancing with assets from countries of the Asia-Pacific region.

Contrasting with other studies on contagion that follow a similar approach, results of this study indicate that important asymmetries are not encountered, and evidence of contagion

is scarce. This result, which goes in line with those of Forbes & Rigobon (2001), suggests that exchange rate co-movements in the region's currencies are due to high interdependence between countries.

Our results suggest that co-movements in Asian economies are mainly derived from their higher connectedness and integration over time. Foreign exchange markets in this region have developed importantly, as currencies of Asian countries have become increasingly important in global investment portfolios composition and in international trading. When comparing our results to those of related studies using countries from other regions, it becomes evident the importance of regional components in contagion. More specifically, exchange rate contagion is more likely to occur within countries of regions with less developed financial markets, as for example Latin America. This result highlights the importance of regional diversification in constructing global hedging strategies in foreign exchange markets.

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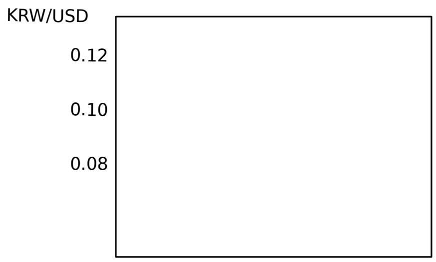
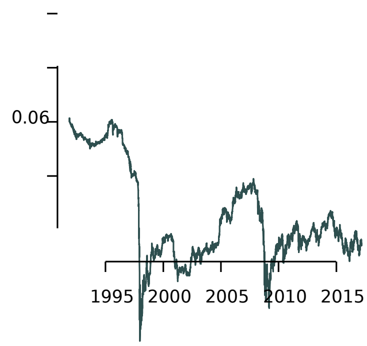
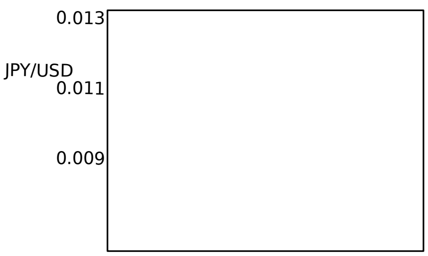
Figure 2. Nominal exchange rates.

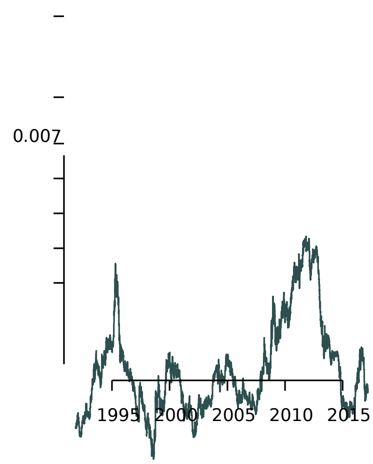
South Korea.



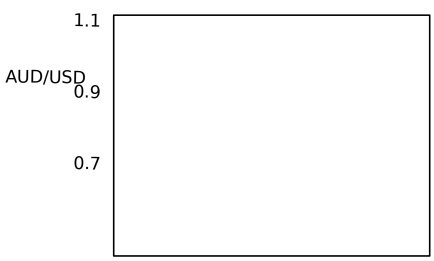


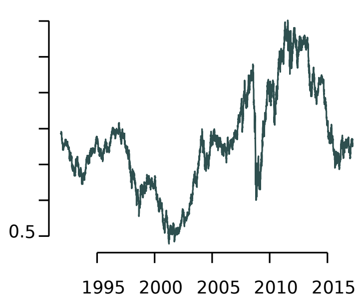
Japan.



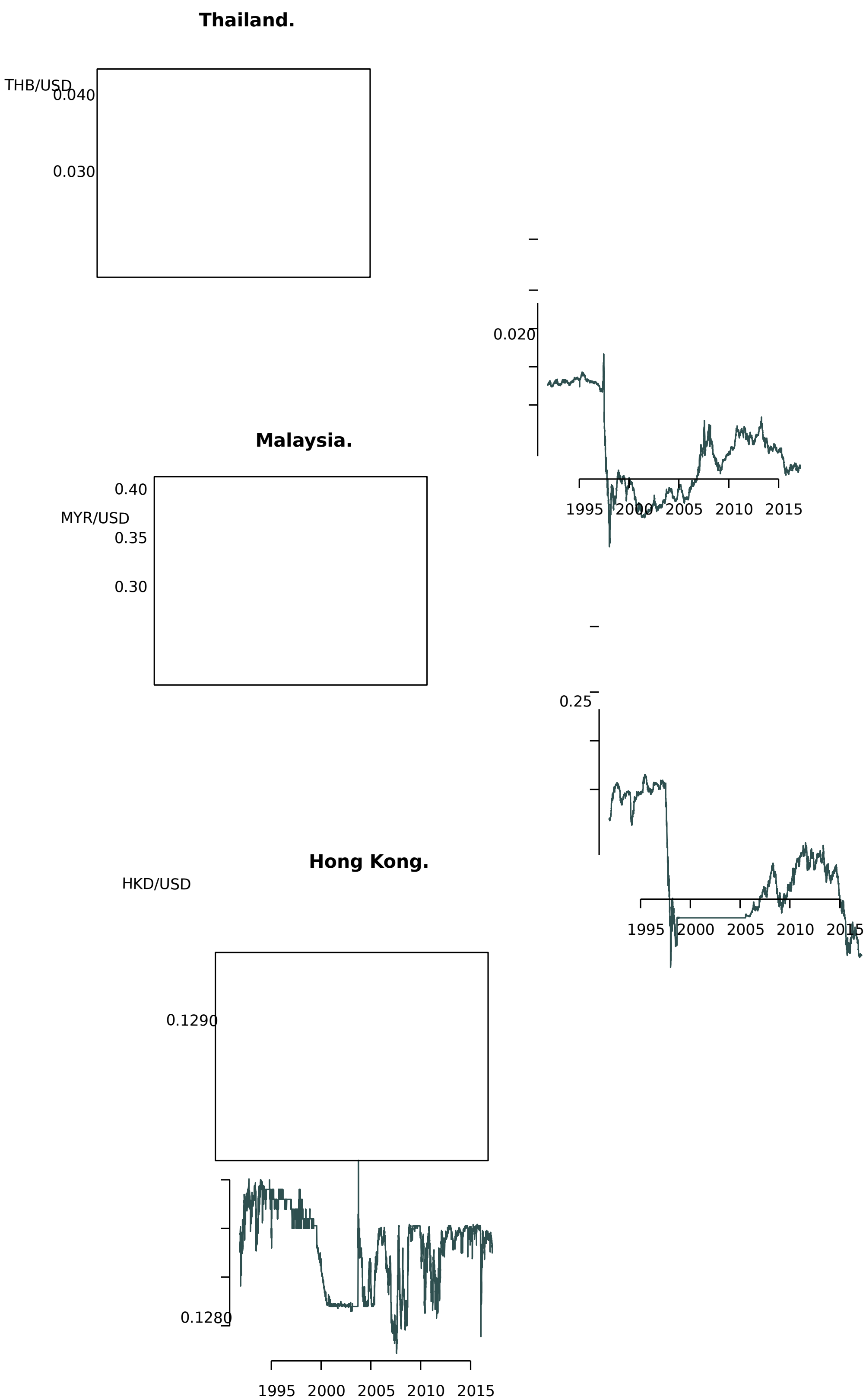


Australia.



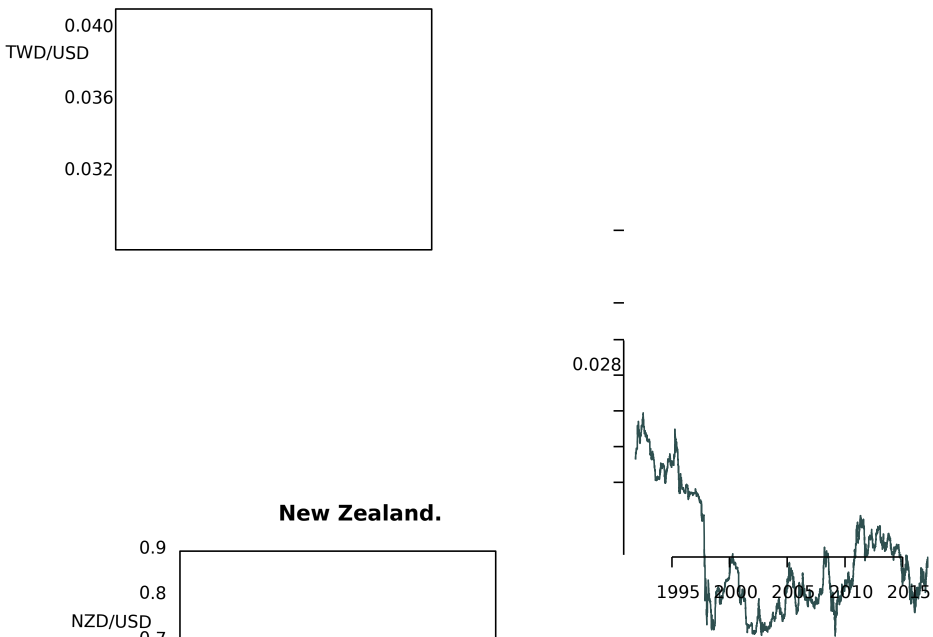


Time Time Time

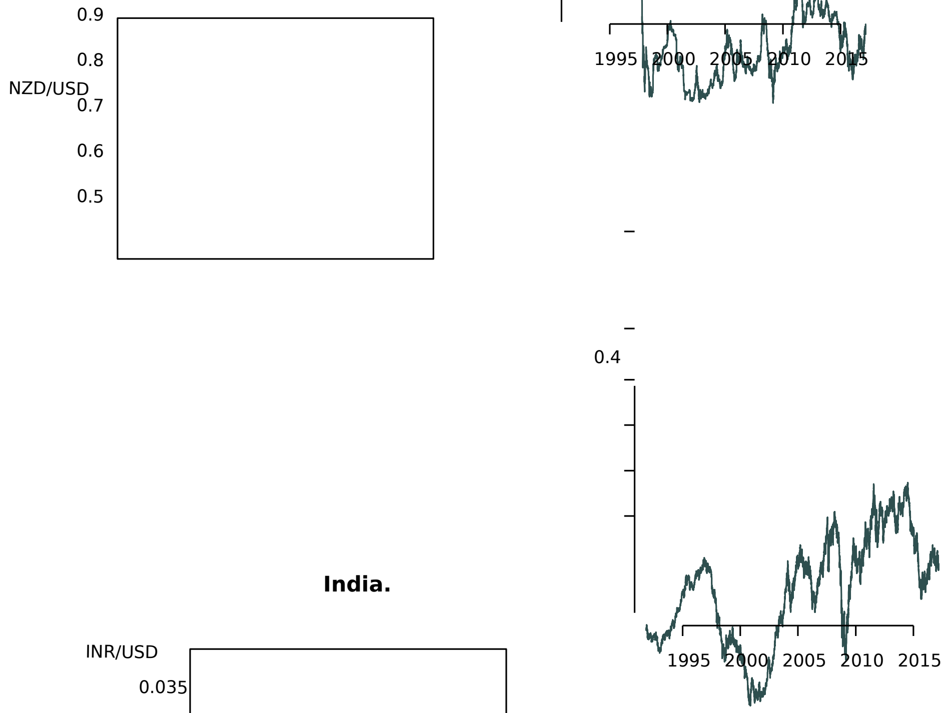

Thailand.
THB/USD
0.040
0.030
0.020
1995 2000 2005 2010 2015
Malaysia.
MYR/USD
0.40
0.35
0.30
0.25
1995 2000 2005 2010 2015
Hong Kong.
HKD/USD
0.1290
0.1280
1995 2000 2005 2010 2015

Time Time Time

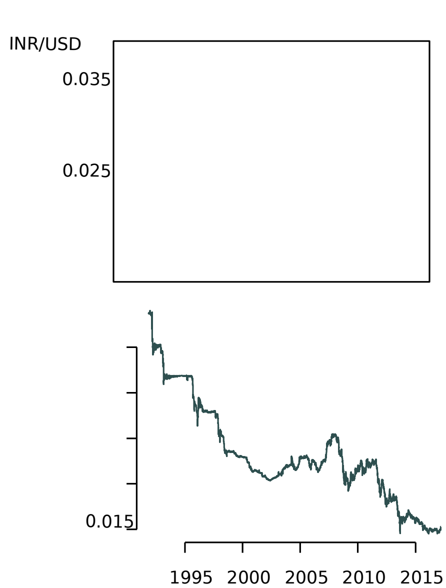
Taiwan.



New Zealand.

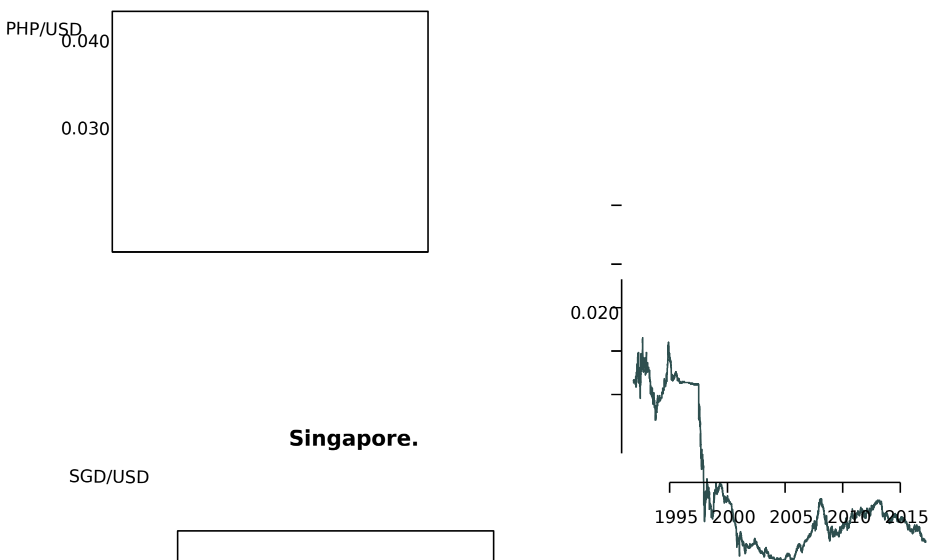


India.

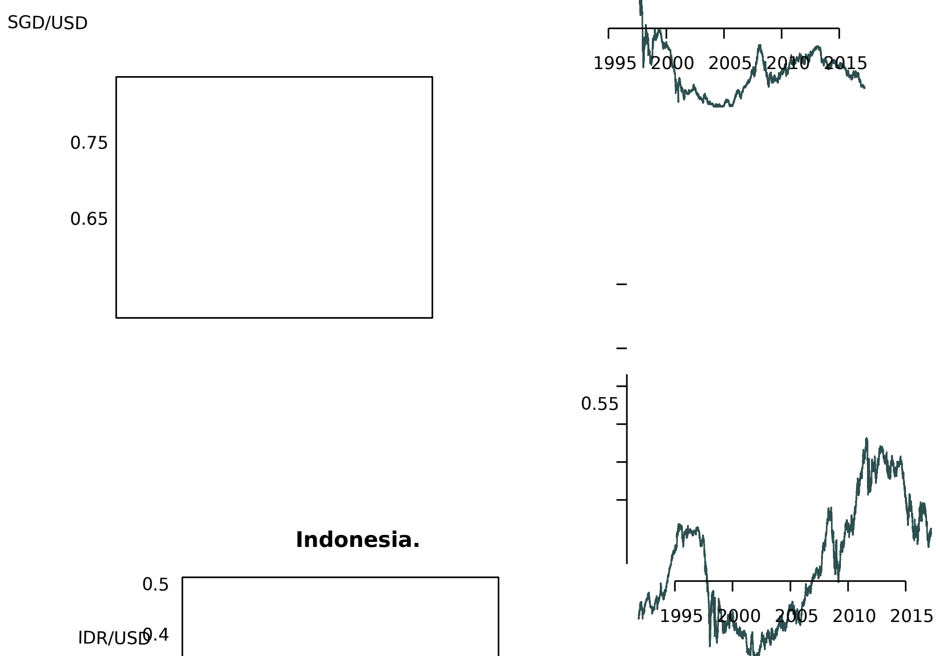


Time Time Time

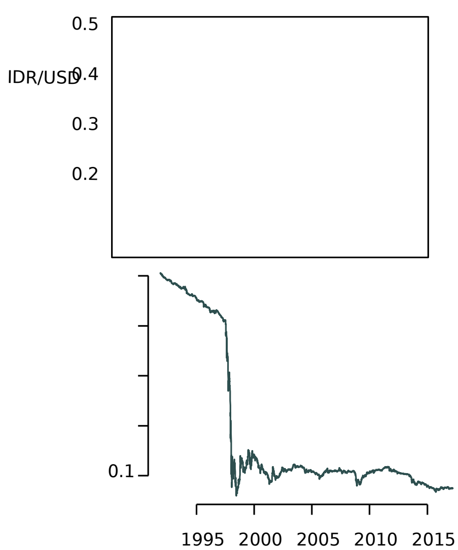
The Philippines.



Singapore.



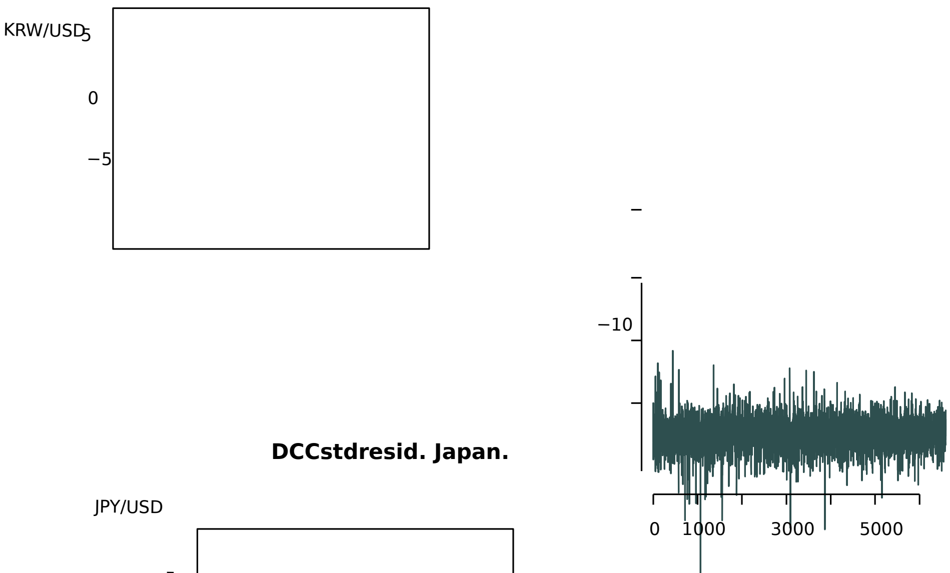
Indonesia.



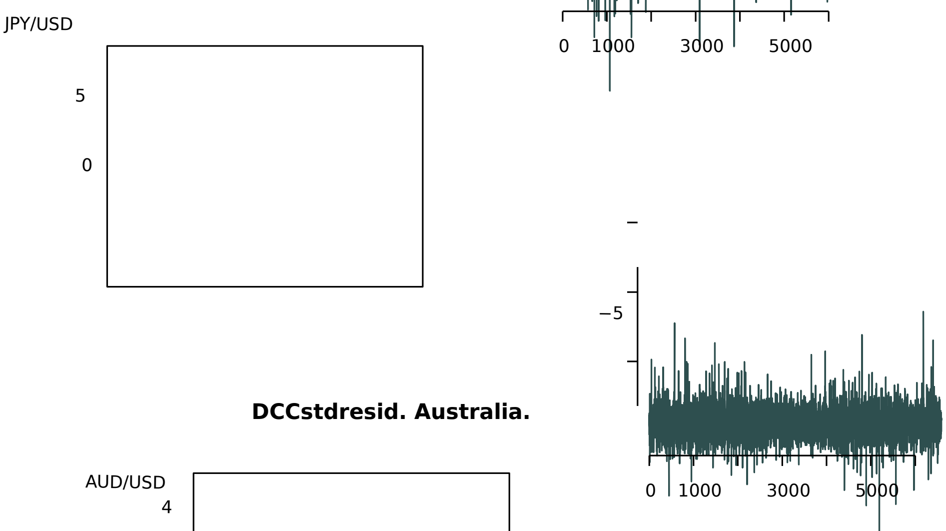
Time Time Time

Figure 3. DCC standard residuals

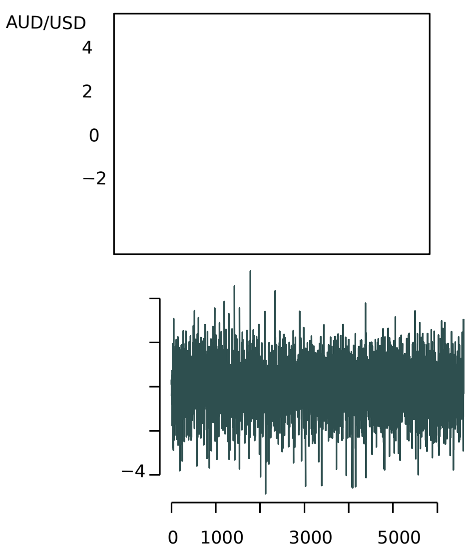
DCCstdresid. South Korea.



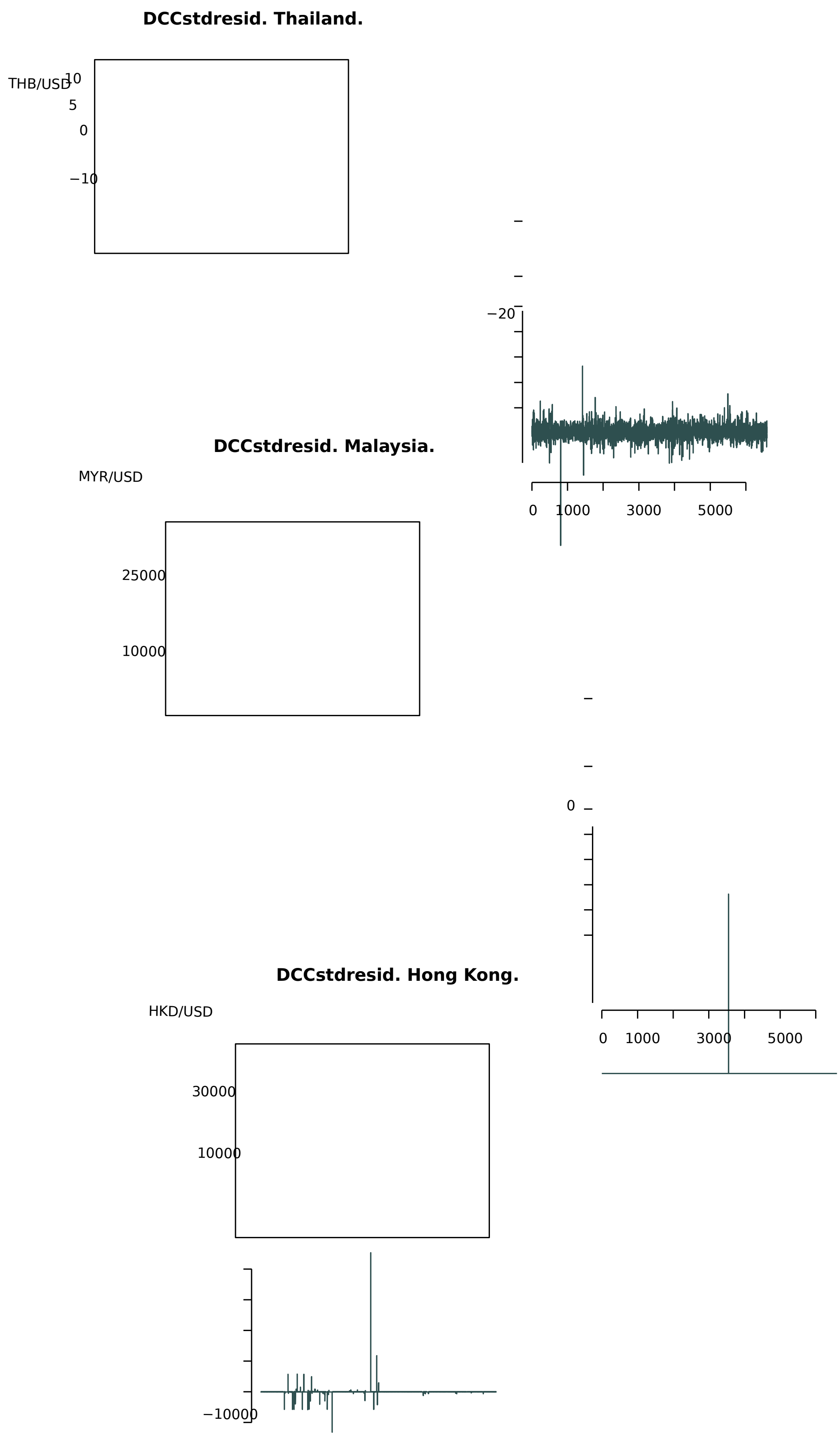
DCCstdresid. Japan.



DCCstdresid. Australia.

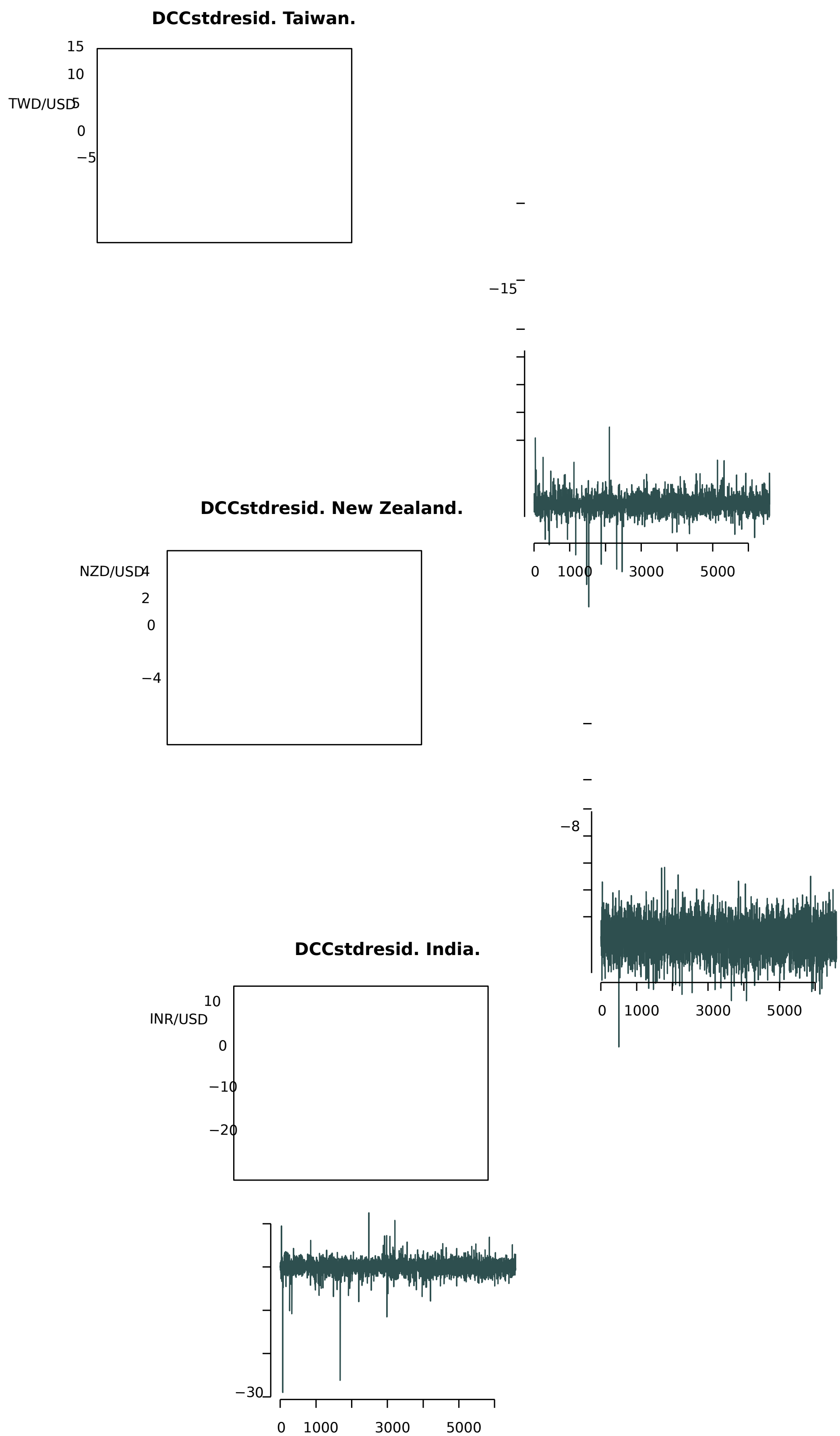


Observations	Observations	Observations


DCCstdresid. Thailand.
THB/USD
10
5
0
−10
−20
0
1000
3000
5000
DCCstdresid. Malaysia.
MYR/USD
25000
10000
0
0
1000
3000
5000
DCCstdresid. Hong Kong.
HKD/USD
30000
10000
−10000

0 1000 3000 5000

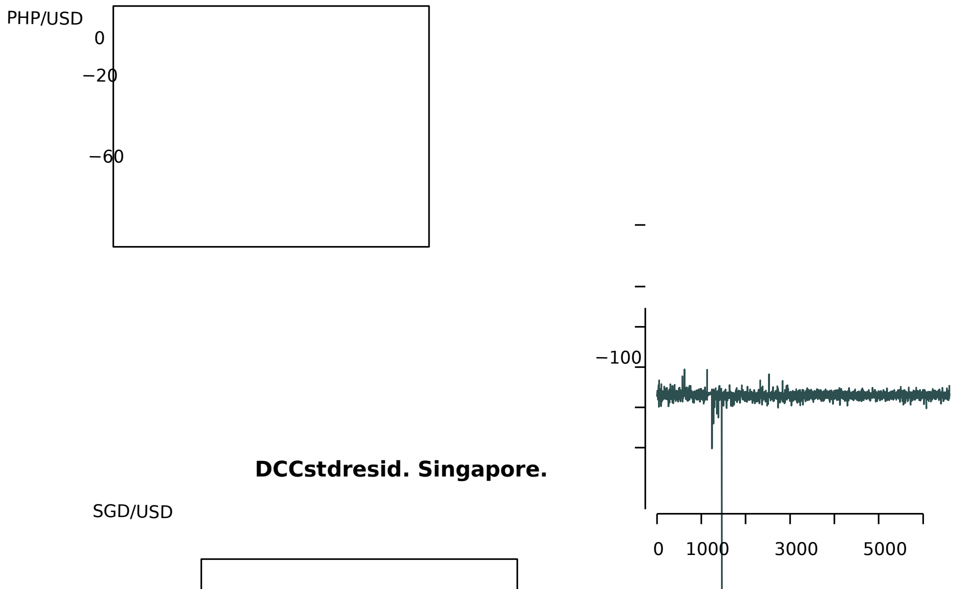
Observations Observations Observations



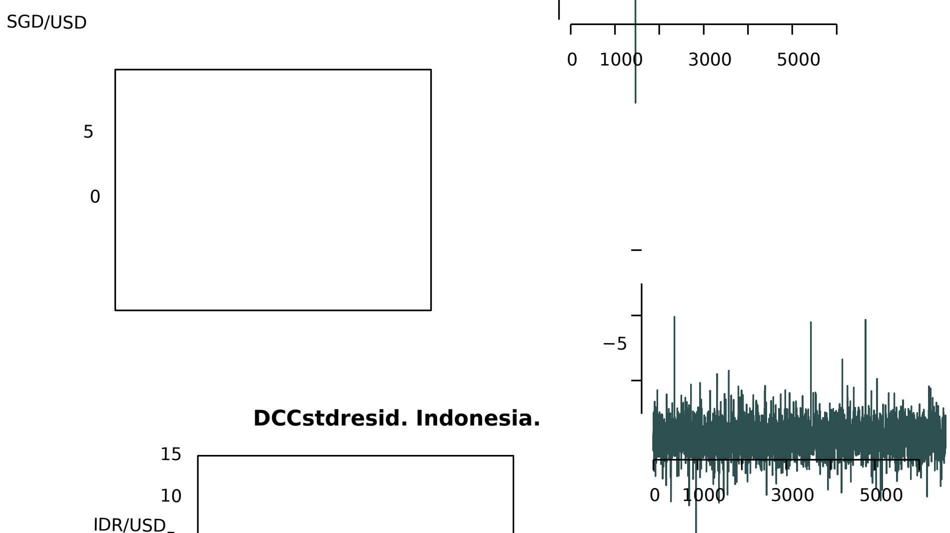
DCCstdresid. Taiwan.
TWD/USD
15
10
5
0
−5
−15
0
1000
3000
5000
DCCstdresid. New Zealand.
NZD/USD
4
2
0
−4
−8
0
1000
3000
5000
DCCstdresid. India.
INR/USD
10
0
−10
−20
−30
0
1000
3000
5000

Observations	Observations	Observations

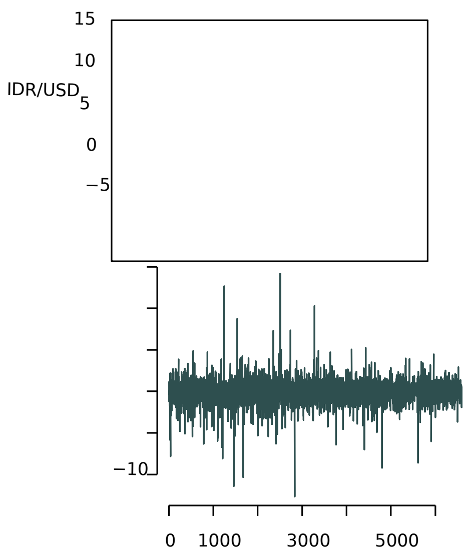
DCCstdresid. The Philippines.



DCCstdresid. Singapore.



DCCstdresid. Indonesia.



Observations Observations Observations

Figure 4. Kendall's taus and contours

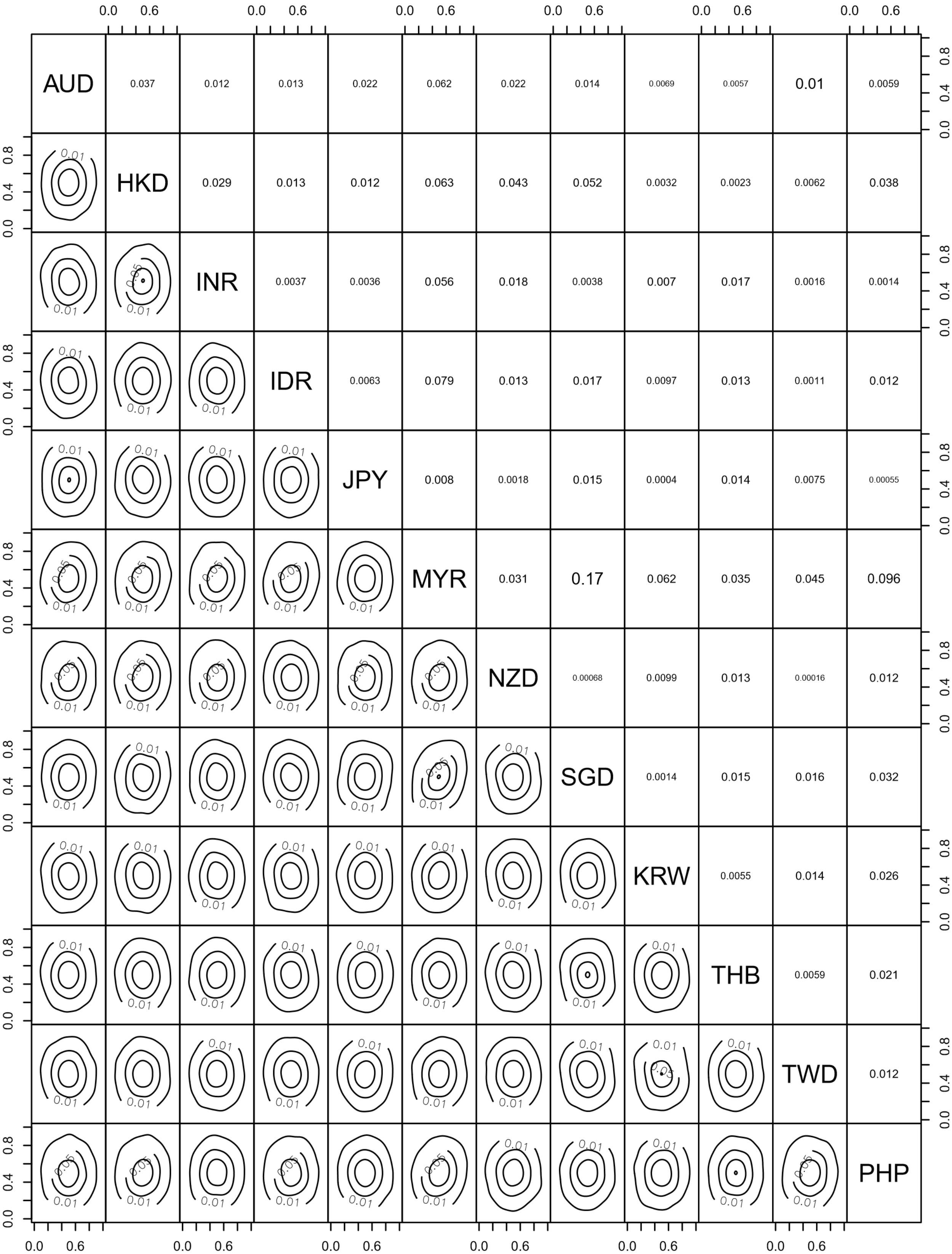

AUD 0.037 0.012 0.013 0.022 0.062 0.022 0.014 0.0069 0.0057 0.01 0.0059
HKD 0.029 0.013 0.012 0.063 0.043 0.052 0.0032 0.0023 0.0062 0.038
INR 0.0037 0.0036 0.056 0.018 0.0038 0.007 0.017 0.0016 0.0014
IDR 0.0063 0.079 0.013 0.017 0.0097 0.013 0.0011 0.012
JPY 0.008 0.0018 0.015 0.0004 0.014 0.0075 0.00055
MYR 0.031 0.17 0.062 0.035 0.045 0.096
NZD 0.00068 0.0099 0.013 0.00016 0.012
SGD 0.0014 0.015 0.016 0.032
KRW 0.0055 0.014 0.026
THB 0.0059 0.021
TWD 0.012
PHP

Table 5. *R-vine*

Tree†	Edge‡	No.	Family	Parameter	Parameter2	Tau
1	1,5	2	t	0.03	8.62	0.02
	6,10	9	BB7	1.06	0.02	0.04
	6,12	2	t	0.15	20.45	0.09
	2,7	20	SBB8	1.26	0.71	0.04
	6,1	2	t	0.09	30.00	0.06
	6,3	14	SG	1.06	0.00	0.06
	6,2	2	t	0.10	27.68	0.07
	6,4	17	SBB1	0.05	1.06	0.08
	6,9	2	t	0.10	16.16	0.06
	6,8	2	t	0.27	9.52	0.17
	11,6	19	SBB7	1.04	0.07	0.05
2	6,5|1	2	t	0.01	18.97	0.01
	8,10|6	2	t	-0.04	13.13	-0.02
	2,12|6	20	SBB8	1.15	0.76	0.03
	6,7|2	20	SBB8	1.06	0.96	0.03
	2,1|6	20	SBB8	1.12	0.87	0.03
	2,3|6	13	SC	0.04	0.00	0.02
	8,2|6	9	BB7	1.03	0.05	0.04
	8,4|6	2	t	-0.06	19.23	-0.04
	8,9|6	2	t	-0.03	17.47	-0.02
	11,8|6	2	t	-0.04	13.97	-0.02
3	2,5|6,1	5	F	-0.12	0.00	-0.01
	4,10|8,6	2	t	-0.03	15.45	-0.02
	3,12|2,6	2	t	-0.01	23.75	0.00
	1,7|6,2	2	t	0.02	14.65	0.01
	3,1|2,6	5	F	-0.15	0.00	-0.02
	8,3|2,6	2	t	-0.02	24.21	-0.01
	4,2|8,6	16	SJ	1.01	0.00	0.01
	9,4|8,6	2	t	-0.02	15.42	-0.02
	11,9|8,6	2	t	-0.02	9.38	-0.02
4	3,5|2,6,1	2	t	-0.00	29.59	-0.00
	2,10|4,8,6	6	J	1.01	0.00	0.01
	8,12|3,2,6	2	t	0.00	29.00	0.00
	3,7|1,6,2	3	C	0.02	0.00	0.01
	8,1|3,2,6	2	t	-0.01	13.06	-0.01
	4,3|8,2,6	33	C270	-0.02	0.00	-0.01
	9,2|4,8,6	2	t	0.00	26.75	0.00
	11,4|9,8,6	2	t	-0.01	28.76	-0.01
5	8,5|3,2,6,1	2	t	0.01	9.22	0.01
	3,10|2,4,8,6	14	SG	1.01	0.00	0.01
	1,12|8,3,2,6	0	I	-	-	0.00
	8,7|3,1,6,2	2	t	-0.02	22.70	-0.01
	4,1|8,3,2,6	5	F	-0.18	0.00	-0.02

LogLik= 1081.76, AIC= -1955.53, BIC=
-1248.98 ‡
1: Australia, 2: Hong Kong, 3: India, 4: Indonesia, 5: Japan, 6: Malaysia, 7: New Zealand, 8: Singapore, 9: South Korea, 10: Thailand, 11: Taiwan, 12: The Philippines.