

Detecting exchange rate contagion using copula functions

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Abstract

We study exchange rate dependencies between seven countries from four different regions of the world. Our sample includes two developed countries, the United Kingdom and Germany (representing the Euro Area), two large emerging Asian economies, South Korea and Indonesia, two Latin American countries, Brazil and Chile, and South Africa. The currencies of all of these countries are actively traded in global forex markets and all of them are important for large international portfolio composition and rebalancing. We construct multivariate copula functions using a regular vine copula approach, allowing for very flexible dependency structures. We find evidence of exchange rate contagion for our set of countries. However, important asymmetries are worth noting. First, contagion occurs only during periods of exchange rate appreciation of the different currencies with respect to the United States Dollar. We do not find evidence of contagion for any pair of exchange rates during periods of currency depreciations. Second, contagion is more frequent in pairs of countries that include either the United Kingdom or Germany. In fact, the largest tail dependence coefficient corresponds to the pair composed by these two countries' exchange rates. Third, contagion occurs more within countries of a same region, for instance, between Brazil and Chile, and between Korea and Indonesia. This result shows that, in episodes of large currency appreciation, hedging strategies for global investors taking positions in large markets require regional diversification.

JEL Classification: C32; C51; E42.

Keywords: *Copula functions; Exchange rate contagion; Emerging and developed economies.*

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Resumen

En el presente trabajo estudiamos las dependencias en tasas de cambio entre siete países de cuatro diferentes regiones del mundo. Nuestra muestra incluye dos países desarrollados, el Reino Unido y Alemania (representando la zona Euro), dos economías emergentes asiáticas, Corea del Sur e Indonesia, dos países latinoamericanos, Brasil y Chile, y Sudáfrica. Las divisas de estos países se cotizan activamente en el mercado global, todas ellas son importantes para la composición y rebalanceo del portafolio internacional. Construimos funciones de copula multivariadas usando una metodología Regular Vine, que permite modelar estructuras de dependencia muy flexibles. Encontramos evidencia de contagio en tasas de cambio para nuestra muestra. Sin embargo, hay asimetrías importantes que se deben tener en cuenta. En primer lugar, el contagio ocurre sólo durante periodos de apreciación de las distintas divisas frente al dólar estadounidense. No encontramos evidencia de contagio durante periodos de depreciación cambiaria. En segundo lugar, el contagio es más frecuente en países que incluyen el Reino Unido y Alemania. El coeficiente de cola más alto corresponde a esta pareja de países. En tercer lugar, el contagio es más frecuente dentro de países de la misma región, por ejemplo, entre Brasil y Chile, y entre Corea e Indonesia. Este resultado muestra que, en episodios de grandes apreciaciones, las estrategias de cobertura para inversionistas globales con posiciones en grandes mercados requieren diversificación regional.

Clasificación JEL: C32; C51; E42.

Palabras Clave: *Funciones copula; Contagio en tasas de cambio; Economías desarrolladas y emergentes.*

1 Introduction

Studying exchange rate correlation is of major importance in financial applications. Investors in international financial markets need reliable estimates for portfolio optimization, as exchange rate movements affect the expected profitability and risk of financial assets. Policy makers require them for economic policy assessment and for international economic policy coordination.

Several studies emphasize that conditional covariances and conditional correlations between assets vary largely over time (for instance, Bollerslev, Engle and Wooldridge, 1988; and, Engle, 2002). Recent studies on exchange rate comovement have shown that conditional correlations in times of financial distress are substantially higher than during normal times (Maya et al., 2015 and Maya et al., 2015). These significant differences have been associated to the effects of financial contagion. The recent global financial crisis, which rapidly spread from the United States subprime mortgage market to other markets all over the world, highlights the relevance of studying financial linkages and contagion in an international context. During that episode of financial distress, contagion among markets developed without following a clear geographical pattern, affecting several markets throughout the world.

While different definitions of contagion coexist in the literature Kenourgios et al. (2015), most recent empirical studies use the definition in Forbes and Rigobon (2002). They associate contagion with a situation in which cross-market linkages significantly increase after the realization of a negative shock. In this context, transmission of crises occurs due to high interdependence among markets. This is an appealing definition because it facilitates empirical testing and distinguishing between temporal and permanent mechanisms of crises' transmission. This differentiation is important for the design and implementation of economic policy actions aimed to prevent or diminish the negative effects caused by external shocks.

We study exchange rate interdependence and contagion using a method that goes beyond a simple analysis of correlation breakdowns. We construct multivariate copula functions using a regular vine copula approach, allowing for very flexible

dependency structures. Regular vines are computed following the methodology proposed by Dissmann et al. 2013. We use daily exchange rate data for a set of seven countries between April 2006 and February 2018. Exchange rates correspond to the relative price of each country's currency with respect to the United States Dollar. The set of countries includes developed as well as large emerging economies. As in Bradley and Taqqu 2004 and Durante and Jaworski 2010, we measure middle and tail dependencies using local correlation coefficients and identify contagion as a situation in which these coefficients are significantly different in statistical terms.

Our contributions to the literature are twofold. First, while various studies have implemented copula approaches for studying exchange rate contagion (see, for instance, Kurowicka and Cooke 2006; Aas et al. 2009; and, Czado et al. 2012), most of them construct C-vines or D-vines, which are particular cases of regular vines. Two exceptions are Loaiza-Maya et al. (2015; 2015), who use R-vines to study exchange rate contagion in Latin American economies. In this sense, our approach is more general than those frequently used in the literature. Second, only a handful of papers have studied exchange rate contagion between developed and large emerging market economies. Up to our knowledge, we are the first among them in implementing a regular vine copula approach.

Our sample includes two developed countries, the United Kingdom and Germany (representing the Euro Area), two large emerging Asian economies, South Korea and Indonesia, two Latin American countries, Brazil and Chile, and South Africa. The currencies of all of these countries are actively traded in global forex markets and all of them are important for large international portfolio composition and rebalancing. Hence, understanding how they comove both in normal times and in times of extreme market outcomes is of major importance for hedging purposes.

We find evidence of exchange rate contagion for our set of countries. However, important asymmetries are worth noting. First, contagion occurs only during periods of exchange rate appreciation of the different currencies with respect to the United States Dollar. We do not find evidence of contagion for any pair of exchange rates during periods of currency depreciations. Second, contagion is more frequent in pairs of countries that include either the United Kingdom or Germany. In fact,

the largest tail dependence coefficient corresponds to the pair composed by these two countries' exchange rates. Third, contagion occurs more within countries of a same region, for instance, between Brazil and Chile, and between Korea and Indonesia. This result shows that, in episodes of large currency appreciation, hedging strategies for global investors taking positions in large markets require regional diversification.

The remainder of the paper is structured as follows. Section 2 describes the data used in the empirical analysis. Section 3 is methodological. Section 4 presents our main findings, and the last section concludes.

2 Data Description

In the empirical application we use exchange rate data for seven countries: Brazil, Chile, Germany, Indonesia, South Africa, South Korea and the United Kingdom. We consider bilateral exchange rates of each local currency with respect to the United States Dollar. We compute daily exchange rate returns as the first difference of logarithmic exchange rates and our sample period begins in April 3 2006 and ends in February 15 2018. Figure 3 in the Appendix shows the behaviour of the exchange rates over time.

We include several control variables in the empirical model following the related literature. Specifically, we use daily information on each country's yield curve slope, stock exchange index return, and the first difference of the five-year credit default swap. We include additionally two global variables, namely the S&P 500's return and the VIX's return. These two variables represent global factors relating to risk aversion and investment opportunities in global financial markets.

Table 1* shows descriptive statistics for the dependent and country-specific control variables. Regarding exchange rates, note that returns are on average positive for all countries except for Germany. Four countries exhibit a positive skewness (Brazil, Chile, South Africa and the United Kingdom), while three present negative

*D: First difference. R: Return

skewness (Germany, Indonesia and South Korea). This fact indicates that exchange rate distributions are asymmetric. Additionally, we report evidence of fat tails, as shown by kurtosis over 3 for each country's exchange rate returns.

The mean value of the first difference of credit default swaps is positive for all countries, except for Indonesia. This fact suggests that credit default swaps increase more than they decrease for most countries during our sample period. Skewness is positive for all but two countries (South Korea and the United Kingdom), and kurtosis are way above 3 in all cases, showing the presence of fat tails. Mean stock exchange returns are all positive, but close to zero, skewness is negative in four cases (Indonesia, South Africa, South Korea and the United Kingdom) and positive in the other three, tails are also fat. Finally, regarding the yield curve's slope, mean values are positive in all cases as expected, and there is evidence of fat tails and skewed distributions.

Table 1: Descriptive statistics

Country	Statistic	D.CDS	R.ER	R.Index	i.Diff
Brazil	Mean	3.58e-03	1.33e-04	2.50e-04	7.70e-01
	Variance	7.40e+01	1.11e-04	2.89e-04	4.44e+00
	Skewness	2.29e+00	3.27e-01	-4.13e-02	-9.18e-02
	Kurtosis	1.01e+02	8.71e+00	9.24e+00	2.65e+00
Chile	Mean	1.08e-02	4.08e-05	3.06e-04	1.14e+00
	Variance	1.74e+01	4.09e-05	1.00e-04	3.31e+00
	Skewness	6.20e-01	4.45e-01	5.06e-02	1.50e+00
	Kurtosis	6.05e+01	7.57e+00	1.50e+01	5.28e+00
Germany	Mean	1.95e-03	-6.44e-06	2.32e-04	1.25e+00
	Variance	2.56e+00	3.72e-05	1.89e-04	2.16e+00
	Skewness	5.83e-02	-8.46e-02	-1.81e-02	1.40e-01
	Kurtosis	2.60e+01	5.07e+00	9.25e+00	2.23e+00

Indonesia	Mean	-2.47e-02	1.33e-04	5.17e-04	1.70e+00
	Variance	2.45e+02	3.21e-05	1.72e-04	3.79e+00
	Skewness	2.97e+00	-1.38e-01	-6.47e-01	1.84e+00
	Kurtosis	1.33e+02	1.94e+01	1.12e+01	1.87e+01
South Africa	Mean	3.45e-02	2.11e-04	3.22e-04	1.12e+00
	Variance	6.52e+01	1.24e-04	1.54e-04	3.25e+00
	Skewness	1.26e+00	1.11e+00	-1.79e-01	-9.18e-01
	Kurtosis	4.35e+01	1.74e+01	5.93e+00	2.83e+00
South Korea	Mean	9.60e-03	3.36e-05	1.82e-04	1.96e+00
	Variance	4.79e+01	5.67e-05	1.58e-04	4.94e+00
	Skewness	-2.46e+00	-7.50e-01	-4.36e-01	-1.47e-02
	Kurtosis	1.87e+02	5.12e+01	1.20e+01	2.24e+00
United Kingdom	Mean	3.42e-03	7.07e-05	6.02e-05	1.53e+00
	Variance	3.79e+00	3.71e-05	1.39e-04	3.74e+00
	Skewness	-1.27e-01	1.10e+00	-1.37e-01	-2.11e-01
	Kurtosis	2.54e+01	1.69e+01	1.11e+01	2.15e+00

3 Empirical methodology

This section presents the copula-based methodology used here for modelling dependence.

3.1 Copula functions

The concept of copula is based on the following theorem.

Sklar's Theorem (1959) Let $F(x_1, \dots, x_n) = P[X_1 \leq x_1, \dots, X_n \leq x_n]$ be a n -dimensional joint distribution function, and let $F_1(x_1), \dots, F_n(x_n)$ be the marginal distribution functions of the continuous random variables X_1, \dots, X_n . If every

marginal distribution function is continuous on the interval $[0, 1]$, then there exists a unique copula function C such that for all x_1, \dots, x_n ,

$$F(x_1, \dots, x_n) = C(F_1(x_1), \dots, F_n(x_n)) \quad (1)$$

3.2 Pair Copula Construction (PCC)

The estimation of high dimensional joint density functions is demanding computationally. Joe (1997) proposed the Regular Vine Copula method, which allows to compute the joint density function, described in Equation (2), as the product of $\frac{n(n-1)}{2}$ bivariate copulas. This approach was further studied by Bedford and Cooke (2001, 2002), Dissmann et al. (2013).

Let $f(x_1, \dots, x_n)$ be a n -dimensional joint density function. This density function can be factorised as:

$$f(x_1, \dots, x_n) = f_n(x_{n-1}) \cdot f_{n-1|n}(x_{n-1}|x_n) \cdot f_{n-2|n-1,n}(x_{n-2}|x_{n-1}, x_n) \cdots f_{1|2,\dots,n}(x_1|x_2, \dots, x_n) \quad (2)$$

Hence, each marginal distribution in Equation(2) can be rewritten as:

$$f(x_i|\nu) = c_{x_i\nu_j|\nu_{-j}}(F(x_i|\nu_{-j}), F(\nu_j|\nu_{-j})) f(x_i|\nu_{-j}) \quad (3)$$

Where, $\nu = \{x_{i+1}, \dots, x_d\}$ is the conditioning set of x_i , ν_j is a variable contained in the set ν , and ν_{-j} are the remaining elements. $c(x_1, x_2)$ is the density of the copula defined as $\frac{\partial C(x_1, x_2)}{\partial x_1 \partial x_2}$.

After replacing Equation(3) in Equation(2), the resulting expression can be referred to as Pair Copula Construction (PCC) and can be represented as a tree[†]. There are several classes of PCCs, the most general one is known as R-Vine copula.

[†]Following Bedford and Cooke (2001), a tree $T = \{N, E\}$ is an acyclical graph where N is its set of nodes, and E its set of edges (unordered pairs of nodes).

3.2.1 R-Vine

An R-vine on n -elements is a nested set of $n - 1$ trees[‡], $\mathcal{V} = (T_1, \dots, T_i, \dots, T_{n-1})$ with a set of edges E_i , and nodes $N_i = \{1, \dots, n - i\} = E_{i-1}$. Furthermore, two nodes in tree $i + 1$ are only connected by one edge if they share a common node in tree i .

R-vine copula. $(\mathbf{F}, \mathcal{V}, B)$ is an R-vine copula specification as defined by Dissmann et al. (2013). $\mathbf{F} = (f(x_1), \dots, f(x_n))$ is a vector of invertible distribution functions, \mathcal{V} is an n -dimensional R-vine as previously defined, and B is a set of bivariate copulas.

The density of an R-vine copula is described by Bedford and Cooke (2001, 2002) as follows:

$$f(\mathbf{x}) = \prod_{k=1}^n f_k(x_k) \prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{m_{i,i}, m_{j,i} | m_{j+1,i}, \dots, m_{n,i}} \left(F_{m_{i,i} | m_{j+1,i}, \dots, m_{n,i}} \left(x_{m_{i,i} | m_{j+1,i}, \dots, m_{n,i}} \right), \right. \\ \left. F_{m_{j,i} | m_{j+1,i}, \dots, m_{n,i}} \left(x_{m_{j,i} | m_{j+1,i}, \dots, m_{n,i}} \right) \right) \quad (4)$$

Where $\mathbf{x} = (x_1, \dots, x_n)$, and $m_{i,j}$ correspond to the elements of the matrix m that represents the R-Vine structure.

Estimation algorithm. As shown by Morales Napoles (2010) there are $\frac{n!}{2} 2^{\binom{n-2}{2}}$ possible R-Vine structures for an n -dimensional problem. Dissmann et al. (2013) propose the following algorithm to efficiently identify and estimate the R-Vine copula:

1. Calculate the empirical Kendall's tau for all possible pair of variables.
2. Select the tree structure that maximizes the sum of the absolute empirical Kendall's tau.
3. Pick and estimate the copula families associated with the tree structure selected in the previous steps. The copulas are selected using the AIC criterion.

[‡]An R-Vine structure can also be represented in a matrix m . See Dissmann et al. (2013).

4. Save the transformed observations for the next tree to be calculated.
5. Repeat these steps to estimate all tree structures.

3.2.2 Tail Dependence Coefficients (TDC)

The tail dependence coefficients indicate the extremal dependence in the upper and lower tails of a joint distribution function. Joe (1997) provides the following definition in terms of copulas.

$$\begin{aligned}\lambda_U &= \lim_{u \rightarrow 1^-} P(X_1 > F_1^{-1}(u) | X_2 > F_2^{-1}(u)) \\ &= \lim_{u \rightarrow 1^-} \frac{1 - 2u + C(u, u)}{1 - u}\end{aligned}\tag{5}$$

$$\begin{aligned}\lambda_L &= \lim_{u \rightarrow 0^+} P(X_1 < F_1^{-1}(u) | X_2 < F_2^{-1}(u)) \\ &= \lim_{u \rightarrow 0^+} \frac{C(u, u)}{1 - u}\end{aligned}\tag{6}$$

The estimation of Equations(5) and (6) is not straightforward in an R-Vine copula context (Caillault and Guégan, 2005). A feasible approach to this problem is to use an empirical copula (non-parametric) $\hat{C}(u, u)$, as defined in Deheuvels (1980):

$$\hat{\lambda}_U = \lim_{i_U \rightarrow N^-} \frac{1 - 2\frac{i_U}{N} + \hat{C}(\frac{i_U}{N}, \frac{i_U}{N})}{1 - \frac{i_U}{N}}\tag{7}$$

$$\hat{\lambda}_L = \lim_{i_L \rightarrow 0^+} \frac{\hat{C}(\frac{i_L}{N}, \frac{i_L}{N})}{1 - \frac{i_L}{N}}\tag{8}$$

To obtain the TDC for an R-Vine copula model we use the following simulation exercise:

1. Given the R-Vine structure we obtain 10,000 simulations of the variables using the algorithms proposed in Dissmann et al. (2013). This exercise is performed

S times.

2. From the previous step we attain 500 trajectories for $\hat{\lambda}_L(\cdot)$ and $\hat{\lambda}_U(\cdot)$, which are used to make a distribution function for each TDC (upper and lower).
3. We calculate the TDCs as the mean of the distribution of the trajectories found in step 2.
4. The confidence intervals $(1 - \frac{\alpha}{2})100\%$ are also obtained from the same empirical distribution function.

3.3 Model for the Marginal Distributions

As explained before, the R-Vine methodology gives us the liberty to choose the marginal distributions for each of the variables. In this case, we model the first two moments of the exchange rate using an ARX(p)-GARCH(1,1) :

$$r.ER_{c,t} = \alpha_{c,0} + \sum_{i=1}^{p_c} \alpha_{c,i} r.ER_{c,t-i} + \sum_{j=1}^{q_c} \beta'_{c,j} X_{c,t-j} + \sum_{j=1}^{q_c} \gamma'_{c,j} Z_{t-j} + \epsilon_{c,t} \quad (9)$$

$$\eta_{c,t} = \epsilon_{c,t} / \sqrt{h_{c,t}} \quad (10)$$

$$h_{c,t} = \omega_{c,0} + \omega_{c,1} h_{c,t-1} + \omega_{c,2} \epsilon_{c,t-1}^2, \quad (11)$$

where $r.ER_{c,t} = \log(r.ER_{c,t}/r.ER_{c,t-1})$, $X_{c,t} = (d.CDS_{c,t}, r.Equity_{c,t}, i.Diff_{c,t})$ and $Z_t = (r.SP500_t, r.VIX_t)$. $ER_{c,t}$ is the exchange rate for country c in period t , $d.CDS_{c,t}$ is the first difference of the credit default swaps, $r.Equity_{c,t}$ is the stock index return, $i.Diff_{c,t}$ is the interest rate differential[§], $r.SP500_t$ is the Standard & Poors 500 index return, and $r.VIX_t$ is the VIX return.

4 Results

Table 2 shows unconditional Pearson's correlation coefficients between pairs of exchange rate. Correlations are high in most cases, indicating that these markets are well integrated. Particularly, Brazil, Chile and South Africa present the highest correlations. This result can be due to the fact that these three countries are important commodity exporters and the value of their currencies depends significantly

[§]Defined as the slope of the zero coupon yield curve.

of the behavior of commodity prices. South Korea is an exception, presenting low correlations with all countries except with the United Kingdom. Although these preliminary results appear to be intuitive and appealing, it is important to remember that unconditional correlations in this context present serious limitations. First, due to the high frequency of the data it is difficult to evaluate the statistical significance of these coefficients. And second, it is also impossible to determine whether correlations are different in normal times and in times of extreme market movements. Copula functions are useful in solving these two limitations of unconditional correlations.

Table 2: Pearson correlation of the exchange rates

	BRA	CHL	GER	INDN	SAFR	SKOR	UK
BRA	1.00	0.91	0.88	0.93	0.94	0.23	0.63
CHL	0.91	1.00	0.81	0.90	0.88	0.38	0.62
GER	0.88	0.81	1.00	0.78	0.81	0.26	0.72
INDN	0.93	0.90	0.78	1.00	0.96	0.32	0.68
SAFR	0.94	0.88	0.81	0.96	1.00	0.33	0.72
SKOR	0.23	0.38	0.26	0.32	0.33	1.00	0.61
UK	0.63	0.62	0.72	0.68	0.72	0.61	1.00

The R-Vine copula structure was identified according to the procedure described above. The selected R-Vine structure is shown in Figure 1 in the Appendix.

Thirty-one families of pair-copulas were considered: Gaussian, t, Clayton, Gumbel, Frank, Joe, Clayton-Gumbel, Joe-Gumbel, Joe-Clayton, Joe-Frank, Survival Clayton, Survival Gumbel, Survival Joe, Survival Clayton-Gumbel, Survival Joe-Gumbel, Survival JoeClayton, Survival Joe-Frank, Rotated Clayton 90 and 270 degrees, Rotated Gumbel 90 and 270 degrees, Rotated Joe 90 and 270 degrees, Rotated Clayton-Gumbel 90 and 270 degrees, Rotated Joe-Gumbel 90 and 270 degrees,

Rotated Joe-Clayton 90 and 270 degrees and Rotated Joe-Frank 90 and 270 degrees.

For selecting the vine copula for each pair of countries, we follow the procedure described in detail in the study by Dissmann et al. (2013). In synthesis, we first select the tree structure by maximizing the sum of the absolute empirical Kendall correlation coefficients using the algorithm proposed by Prim (1957). Then we choose the pair-copula families associated with the tree specified in the previous step, by minimizing the AIC (we follow this goodness-of-fit test for selecting the copulas).

Regarding estimation, the parameters of the selected copulas are estimated by maximum likelihood methods. The transformed observations that will be used in the next tree are calculated using Equation (1). Note that specification tests for the standardized residuals are provided in tables 5 and 6. These steps (those for selection and those for estimation of the vine) are repeated using the transformed observations for all of the remaining trees of the regular vine. The estimated parameters of the bivariate copulas of the R-Vine described in Figure 1 are displayed in Table 4. Most of the parameters of the conditional and unconditional pair-copulas are significant.

Based on the estimated regular vine copula, the tail dependence coefficients (TDCs) were obtained using the simulation procedure explained above. This exercise includes $S = 500$ simulations of $N = 10,000$ observations of a seven-dimensional vector. The TDCs were calculated for the thresholds $i_{L/N}^* = 0.01$ and $i_{U/N}^* = 0.99$.

The upper tail dependence coefficients of our seven exchange rates are displayed in the top right panel of Table 3. These coefficients are associated with the currencies comovement in large depreciations. None of these coefficients are statistically significant at conventional levels. This result indicates that exchange rates do not co-move more during large depreciations. The lower tail dependence coefficients associated with large appreciations are presented in the bottom left panel of Table 3. In contrast with the upper tail case, most of them are significant at the 5% significance level. This result suggests that during periods of extreme currency

appreciation with respect to the United States Dollar, currencies co-move more than during normal times. Hence, diversification opportunities for investors interested in these currencies are significantly reduced during times of extreme currency appreciation. An interesting case deals with Indonesia and South Korea. TDCs between pairs of exchange rates including either Indonesia or South Korea are non-significant, except for the pair containing both countries.

Table 3: Tail dependence parameters for 7 countries R-Vine

	BRA	CHL	GER	INDN	SAFR	SKOR	UK
BRA		0.093	0.102	0.057	0.191	0.064	0.095
CHL	0.082*		0.085	0.053	0.127	0.053	0.077
GER	0.115*	0.073*		0.062	0.202	0.058	0.254
INDN	0.01	0.008	0.015		0.056	0.124	0.057
SAFR	0.189*	0.118*	0.2*	0.008		0.06	0.151
SKOR	0.01	0.009	0.008	0.119*	0.009		0.056
UK	0.069*	0.049*	0.256*	0.017	0.105*	0.008	

Our findings are similar to those of other related studies, such as Loaiza-Maya et al. (2015; 2015). The asymmetric behaviour of capital inflows in episodes of high and low global risk aversion and the different response of emerging countries' central Banks during periods of local currency appreciation and depreciation are probably explaining these appealing empirical findings.

The recent literature on push and pull factors behind foreign portfolio investment decisions has highlighted the fact that while international investors consider carefully recipient countries' fundamentals for investment decisions during times of high global risk aversion, they focus less on fundamentals for making decisions on entering emerging market economies during times of low global risk aversion. Thus, in moments in which there is more appetite for assuming risks it is common to

observe large capital inflows to various emerging markets, and local currency appreciation becomes a common factor in these economies.

As a response to the observed local currency appreciation and to expectations of further appreciation, central banks in developing countries participate actively in foreign exchange markets buying dollars and building up high levels of international reserves. Central bank intervention occurs more commonly during episodes of currency appreciation than during episodes of currency depreciation given the “fear of appreciation” encountered by Levy-Yeyati, Sturzenegger, and Gluzmann (2013), among other studies. Thus, more dependence is observed among exchange rates during periods of local currency appreciation.

As shown by several studies, during times of intensive central bank intervention in foreign reserve markets, financial phenomena such as momentum strengthen in financial markets (see, for instance, Gómez-González and García-Suaza (2012)). And when several central banks are intensively accumulating foreign reserves at the same time, it is more possible to observe “coordinated” side effects of these interventions that may probably influence contagion in foreign exchange markets.

As expected, dependence is lower for Indonesia and South Korea, given peculiarities that make the behaviour of their exchange rates different from those of the other countries included in our sample. Our results shed light for international investors as they show that diversification opportunities in global markets are higher during times of extreme depreciation than during times of extreme currency appreciation.

5 Concluding Remarks

This study implements a regular vine copula approach to evaluate the level of contagion between pairs of exchange rates of seven countries, namely Brazil, Chile, Germany, Indonesia, South Africa, South Korea and the United Kingdom. We measure contagion in terms of tail dependence coefficients, following Fratzscher’s

(2003) definition of contagion as increases in interdependence in times of extreme market movements.

All of the estimated upper-tail dependence coefficients are statistically no-significant. This result indicates that currency co-movements during large depreciations are not significantly different than during normal times. On the contrary hand, almost every lower tail dependence coefficient, associated with large appreciations, is significant at the 5% significance level. Consequently, correlations between pairs of currencies are significantly greater during large appreciations. This means that diversification opportunities for investors interested in these currencies are significantly reduced during times of extreme currency appreciation. Exceptions are encountered in tail dependence coefficients including either Indonesia or South Korea. All of them are non-significant, except for the pair containing both countries.

Our findings are similar to those of other related studies, such as Loaiza-Maya et al. (2015; 2015). The asymmetric behaviour of capital inflows in episodes of high and low global risk aversion and the different response of central Banks during periods of local currency appreciation and depreciation, due to the “fear of appreciation”, are probably explaining these appealing empirical findings.

Finally, our results shed some light on possible diversification strategies that can be followed by international investors. The fact that there is no larger exchange rate dependence during moments of local currencies’ depreciation illustrates that exchange risk diversification can be achieved when taking position in assets of the different countries included in our sample during these periods of time. In episodes of large currency appreciations diversification opportunities are reduced. However, they are achievable between Asian countries and the rest of the world.

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Appendix A Tree Structure

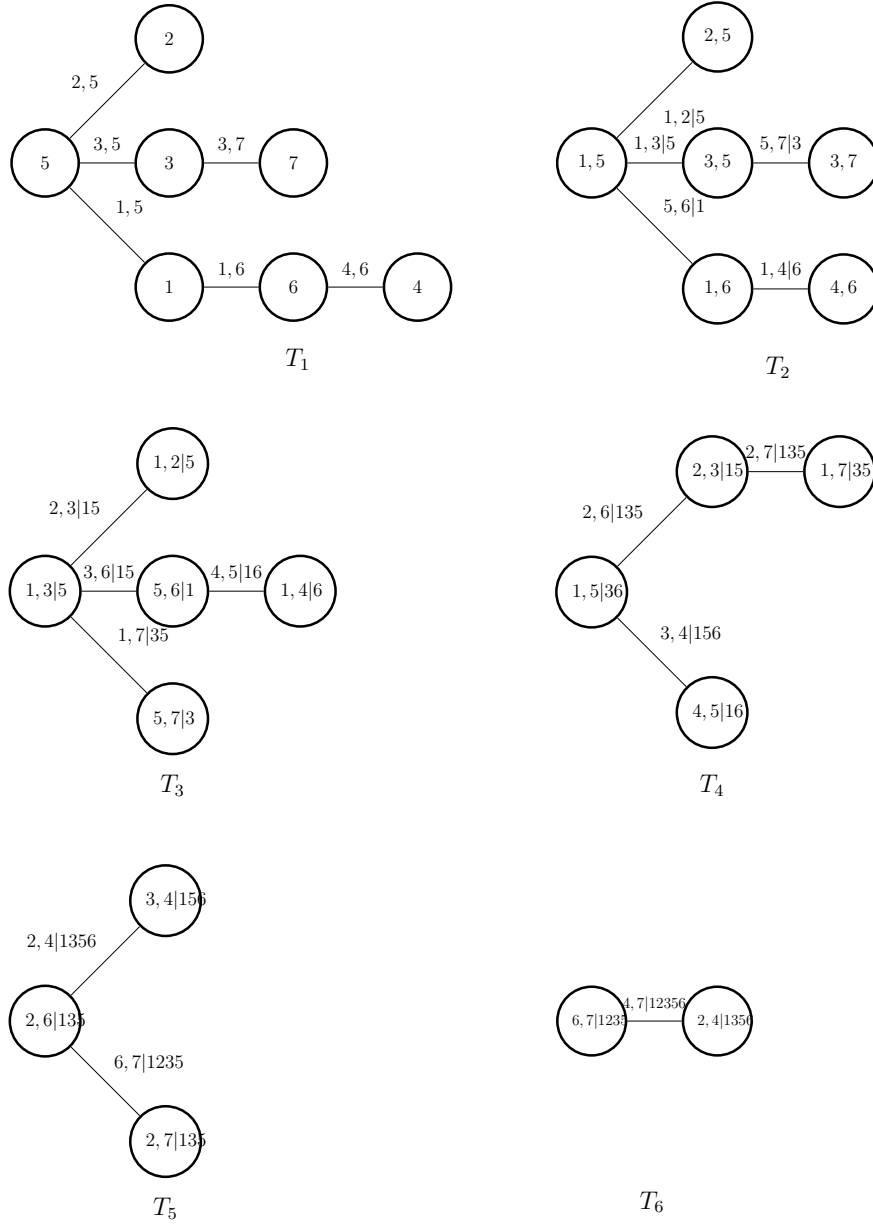


Figure 1: Estimated regular vine. The numbers indicate the exchange rates of the 7 countries as follows: 1=BRA, 2=CHL, 3=GER, 4=INDN, 5=S.AFR, 6=S.KOR, 7=UK

Appendix B R-Vine Specification

Table 4: Regular Vine Specicication

	Copula	Param1	Param2	sd1	sd2
BRA_CHL	Survival Joe-Frank	2.854*	0.474*	1.234	0.204
BRA_GER	Survival Joe-Frank	1.314*	0.896*	0.094	0.059
BRA_INDN	Rotated Clayton 270 degrees	-0.009	-	0.017	-
BRA_SAFR	t	0.515*	12.756*	0.013	2.506
BRA_SKOR	Survival Clayton	0.059*	-	0.018	-
BRA_UK	Gumbel	1.017*	-	0.009	-
CHL_GER	Survival Joe-Frank	1.352*	0.747*	0.302	0.246
CHL_INDN	Rotated Clayton 270 degrees	-0.029	-	0.018	-
CHL_SAFR	t	0.409*	22.124*	0.015	8.903
CHL_SKOR	Frank	-0.126	-	0.108	-
CHL_UK	Frank	0.193	-	0.109	-
GER_INDN	Clayton	0.035	-	0.019	-
GER_SAFR	t	0.433*	6.45*	0.015	0.806
GER_SKOR	Rotated Gumbel 270 degrees	-1.016*	-	0.009	-
GER_UK	t	0.609*	11.685*	0.011	2.354
INDN_SAFR	Rotated Clayton 90 degrees	-0.026	-	0.017	-
INDN_SKOR	t	0.361*	12.558*	0.016	2.947
INDN_UK	Clayton	0.029	-	0.019	-
SAFR_SKOR	Frank	-0.299*	-	0.108	-
SAFR_UK	Joe-Frank	1.376*	0.892*	0.117	0.063

SKOR_UK Rotated Clayton 90 degrees -0.025 - 0.018 -

Appendix C Tests on residuals

Table 5: Univariate Specification tests for the standardized residuals

	ARCH (LM)	Portmanteau
	(lags = 45)	(lags = 250)
BRA	0.833	0.17
CHL	0.202	0.085
GER	0.036	0.269
INDN	0.162	0.02
SAFR	0.404	0.066
SKOR	0.419	0.014
UK	0.823	0.836

Table 6: Multivariate Specification tests for the standardized residuals

	Null Hypothesis	Lags	Statistic	P-Value
Portmanteau	No autocorrelation	300	14795.691	0.191
LM (square residuals)	No MGARCH effect	100	5006.198	0.142

Appendix D Graphics

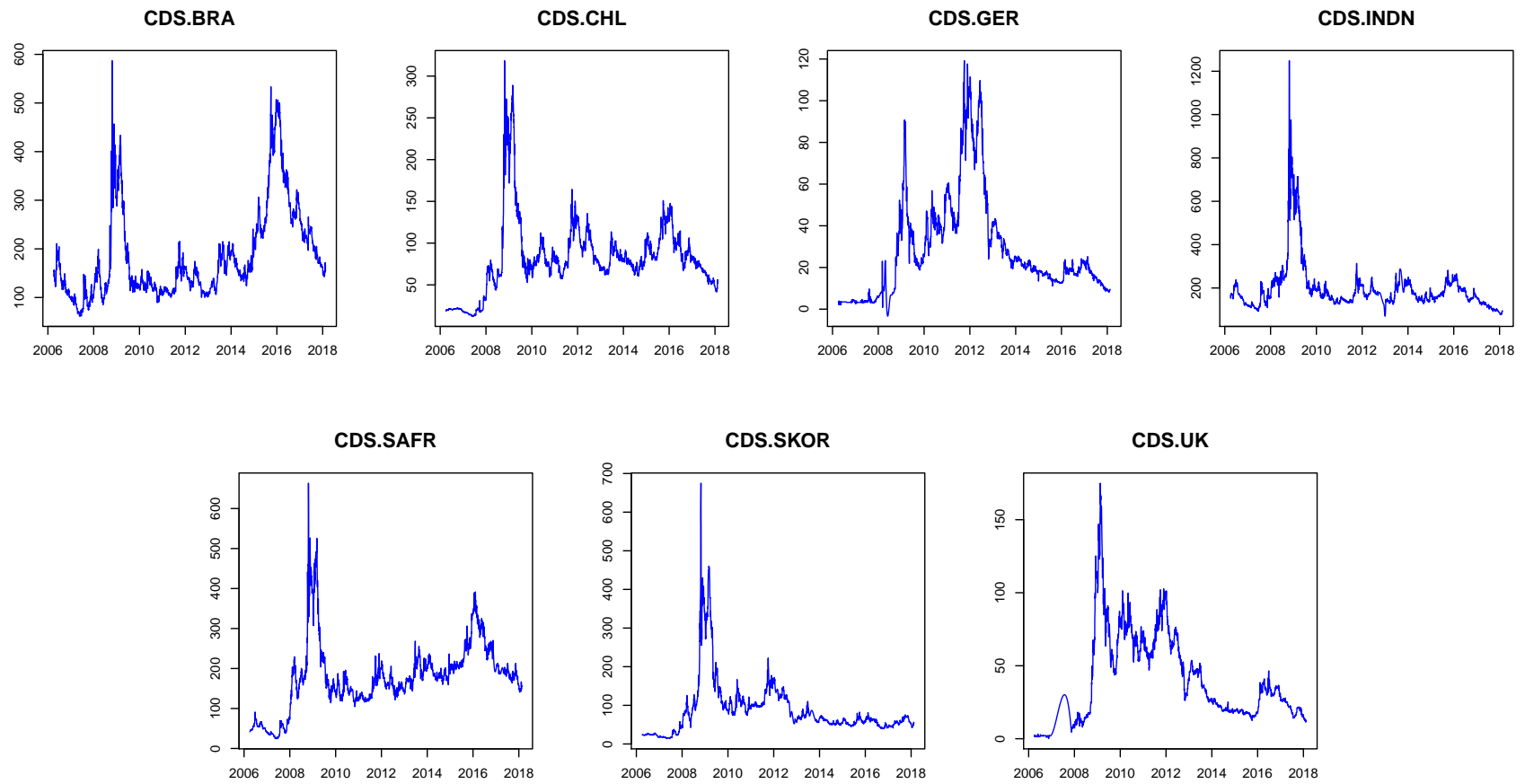


Figure 2: Credit default swaps (5 years) for 7 countries

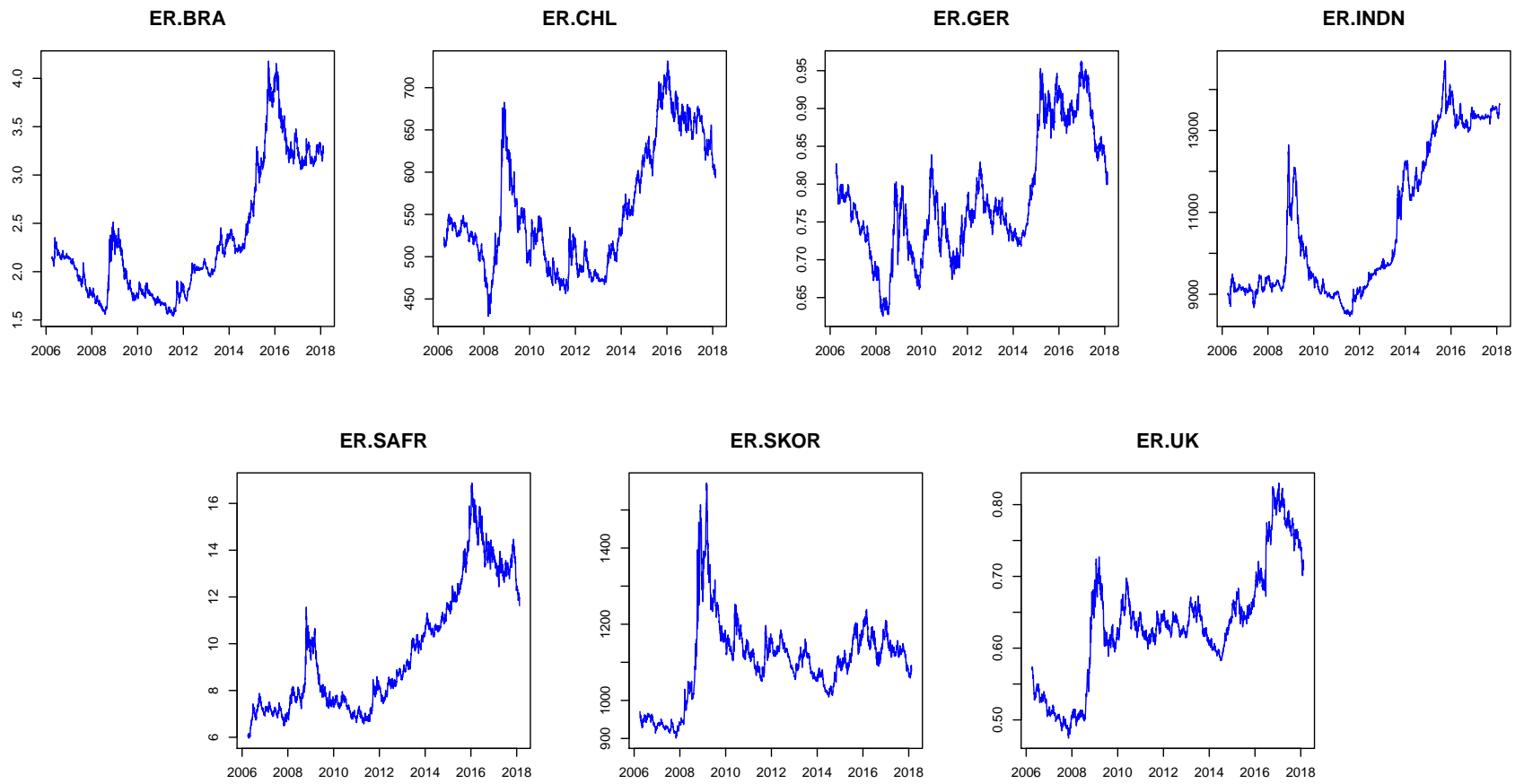


Figure 3: Exchange rates yields for 7 countries

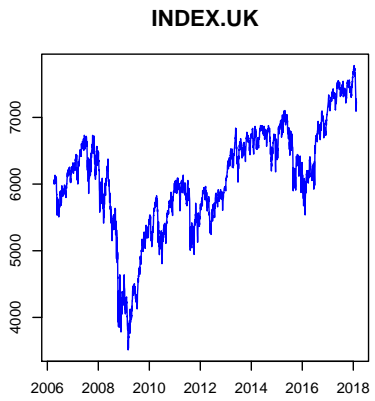
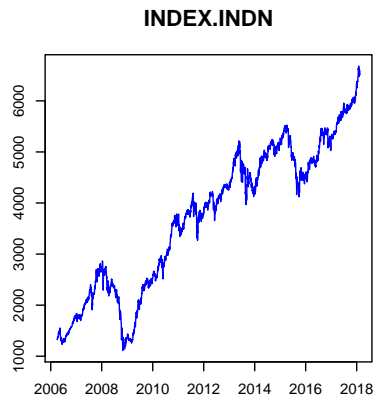
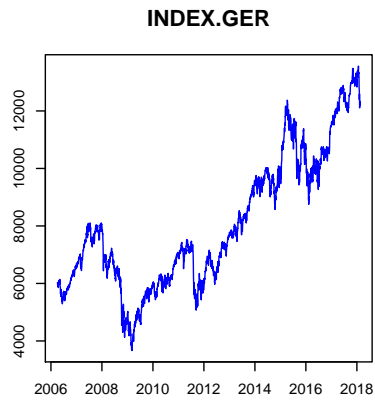
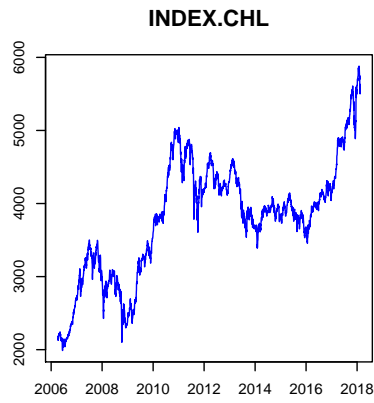
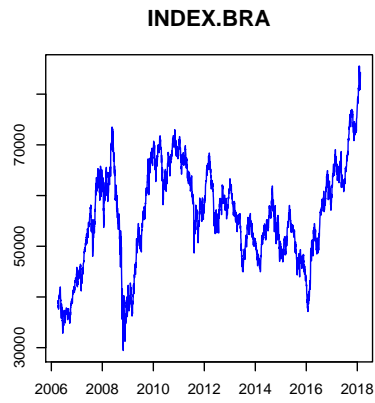


Figure 4: Index for 7 countries

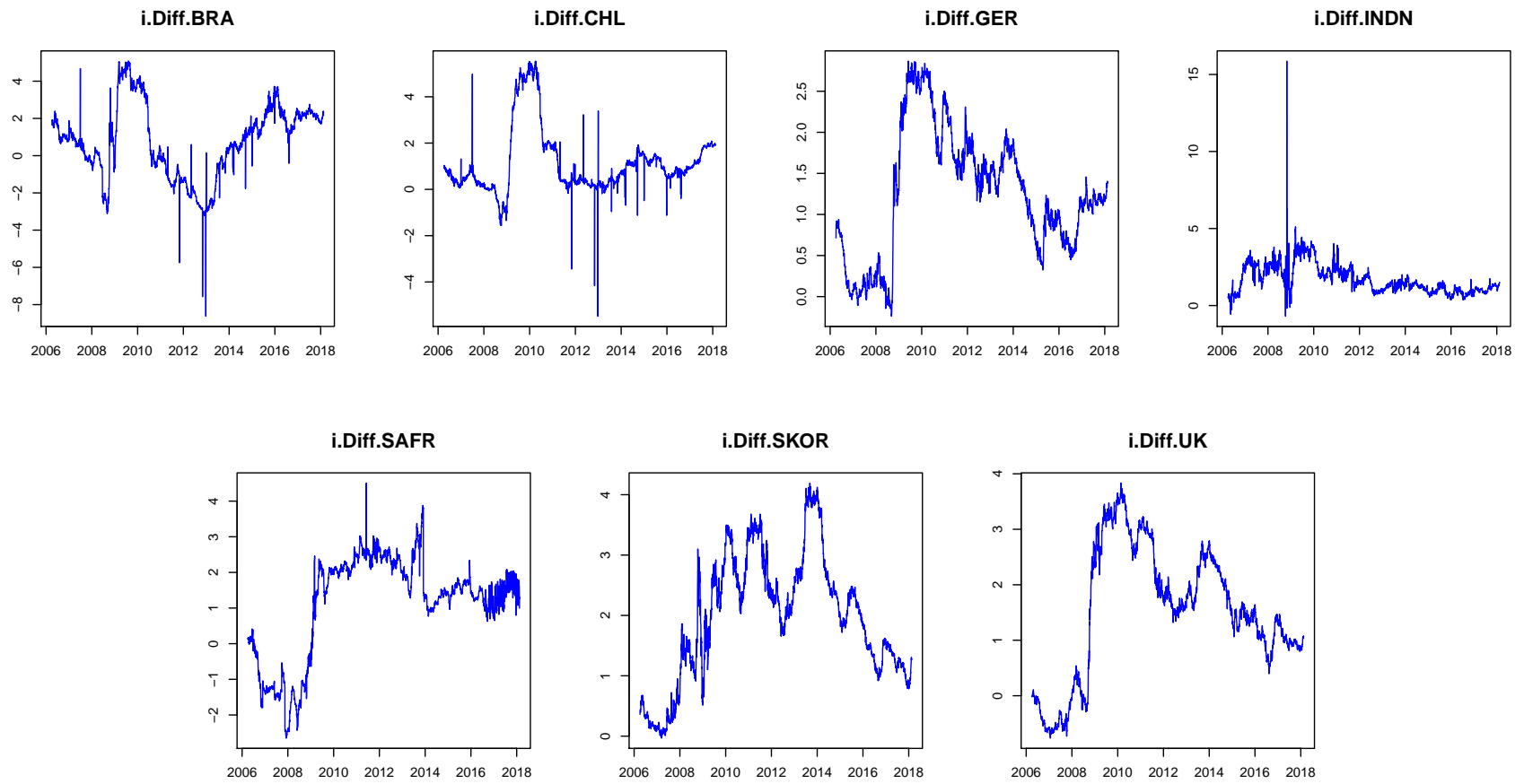


Figure 5: Interest rate differential for 7 countries

