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Detecting exchange rate contagion using copula functions☆

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ABSTRACT

We study exchange rate dependence for 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. 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 during episodes of large currency appreciation hedging strategies for global investors taking positions in large markets requires of regional diversification.

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. Policymakers 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, & Wooldridge, 1988; 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 (Loaiza-Maya, Gómez-González, & Melo-Velandia, 2015a, 2015b). 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

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throughout the world.

While different definitions of contagion coexist in the literature, 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, Brechmann, Czado, and Kurowicka (2013).[1] 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 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 traded actively in global forex markets and all of them are important for international portfolio composition and rebalancing. Hence, understanding how they co-move both in normal times and in times of extreme market outcomes is of major importance for hedging purposes. Specifically, understanding how these currencies co-move in normal times and during times of extreme market turbulence is useful for designing efficient time-varying trading strategies in global financial markets.

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. This result can derive from asymmetries in central bank intervention policies. As shown by Levy-Yeyati, Sturzenegger, and Gluzmann (2013), the fear of appreciation makes central bank intervention more frequent during times of the United States Dollar depreciation, especially in emerging markets and in commodity-dependent economies. Hence, more synchronization in exchange rate markets is expected during times of currency appreciation with respect to the United States Dollar.

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. This highlights the importance of these countries in global exchange rate markets, and indicates that emerging markets' currencies are importantly affected by innovations originating in developed countries' currencies. Third, contagion occurs more within countries of a same region, for instance, between Brazil and Chile, and between Korea and Indonesia. This finding illustrates two interesting things. On the one hand, geographical closeness matters for contagion. Although financial shocks spread within regions in highly connected markets, distance matters for contagion. This result reflects the fact that international financial investors make geographical considerations while managing their portfolio strategies. On the other hand, this result shows that in episodes of large currency appreciation, hedging strategies for global investors taking positions in large markets require regional diversification.Dimitriou and Kenourgios (2013) and Dimitriou, Kenourgios, and Simos (2017) further 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.

Our contributions to the literature are threefold. First, while various studies have implemented copula approaches for studying exchange rate contagion (see, for instance, Kurowicka & Cooke, 2006; Aas, Czado, Figressi, & Bakken, 2009; Panagiotelis, Czado, & Joe, 2012), most of them construct C-vines or D-vines, which are particular cases of regular vines. Two exceptions are Loaiza-Maya et al. (2015a, 2015b), 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. Moreover, we include countries from four different regions of the world. Hence, we study whether contagion follows a geographical pattern, i.e. whether contagion is more likely between nearby countries. Papers focusing in a particular region of the world cannot appropriately test for the geographical component of contagion, as they do not have inter-regional variation. Finally, we show that contagion occurs only during periods of currency appreciation. This fact confirms that higher exchange rate co-movements are not only due to higher foreign exchange markets' integration. Otherwise, there should be no difference in interdependence during devaluations and appreciations.

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.

[1] Different approaches are used in the literature of contagion, such as copula functions, multivariate GARCH models, and others. Among copula function approaches, some use C-vines and D-vines, others R-vines, others dynamic copulas with and without regime switching. Each approach has advantages and disadvantages. We follow an R-vine approach as it is general enough for our purposes and is used in the more closely related studies. Hence, we can compare our results with those of these studies more directly.

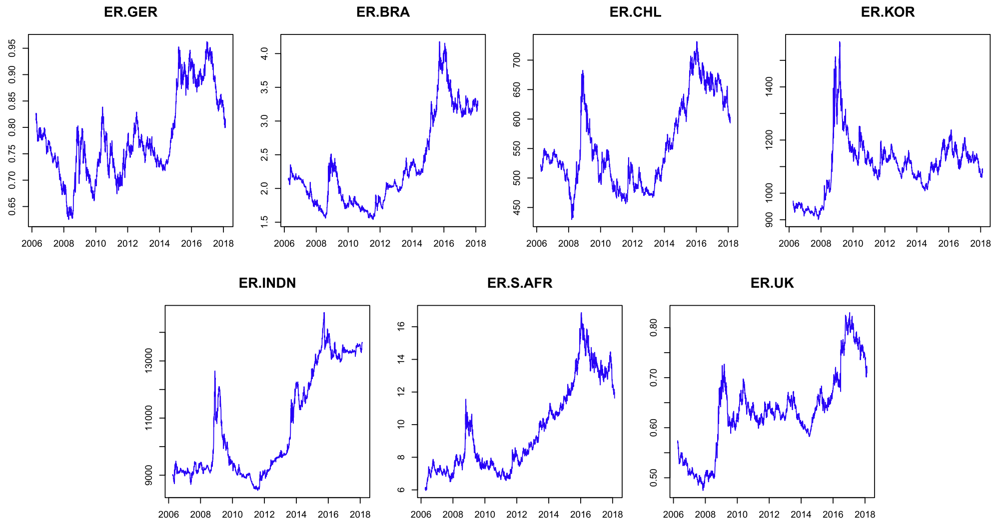

Fig. 1. Exchange rates yields for 7 countries.

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 chose those countries because their currencies are actively traded in international financial markets, and because they are representative of their regions. Germany and the United Kingdom are the two major European economies. Brazil and Chile are the two South American countries with the most developed financial markets. South Africa is an important emerging market, member of the BRICS. South Korea and Indonesia are important Asian economies. Japan and China were not included in the sample due to some characteristics that do not make them suitable for this analysis. The former has had a long-lasting liquidity trap that has forced the central bank to conduct unconventional monetary policies for a very long term. The latter has had an extremely active policy of exchange rate intervention, making it a country in which a free-floating exchange rate policy has not been fully implemented.

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. While some recent papers argue that results from hypothesis tests in finance are frequency dependent (see, for instance, Narayan & Sharma, 2015; Narayan, Ahmed, & Narayan, 2015), daily data contain richer information than data in lower frequencies (see Bannigidadmath & Narayan, 2016; Kenourgios, Naifar, & Dimitriou, 2016). Our sample period begins in April 3 2006 and ends in February 15 2018. Fig. 1 shows the behavior of the exchange rates over time. All currencies, except the South Korean Won, exhibit a derpreciation trend over the sample period. However, all currencies present high-time variation with respect to the United States Dollar, as all of these countries have free-floating exchange rate schemes.

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. The inclusion of these variables allows us to control for fundamental factors explaining exchange rate variation. This permits us to identify exchange rate contagion in a cleaner way.

Table 1[2] shows descriptive statistics forexchange rates and for country-specific control variables included in our empirical model. Regarding exchange rates, note that returns are on average positive for all countries except for Germany. ADF test results, not reported in the table, indicate that returns are stationary. Four countries exhibit a positive skewness (Brazil, Chile, South Africa and the United Kingdom), while three present negative 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. Hence, country risk increased over the sample period in most cases, mainly due to the occurrence of the Subprime and European bonds' financial crises. 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, and 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.

[2] D: First difference. R: Return

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 (Sklar, 1959) Let $F(x_1, \cdots, x_n) = P[X_1 \leqslant x_1, \cdots, X_n \leqslant x_n]$ be a n-dimensional joint distribution function, and let $F_1(x_1), \cdots, F_n(x_n)$ be the marginal distribution functions of the continuous random variables $X_1, \cdots, X_n$. If every marginal distribution function is continuous on the interval [0, 1], then there exists a unique copula function C such that for all $x_1, \cdots, x_n$,

$$F(x_1, \cdots, x_n) = C(F_1(x_1), \cdots, F_n(x_n)) \tag{1}$$

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 Eq. (2), as the product of $\frac{n(n-1)}{2}$ bivariate copulas. This approach was further studied by Bedford and Cooke (2001, 2002) and Dissmann et al. (2013).

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

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

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

$$f(x_i|\boldsymbol{\nu}) = c_{x_i \nu_j|\boldsymbol{\nu}_{-j}}(F(x_i|\boldsymbol{\nu}_{-j}), F(\boldsymbol{\nu}_j|\boldsymbol{\nu}_{-j})) f(x_i|\boldsymbol{\nu}_{-j}) \tag{3}$$

where, $\boldsymbol{\nu} = \{x_{i+1}, \ldots, x_d\}$ is the conditioning set of x_i, ν_j is a variable contained in the set $\boldsymbol{\nu}$, and $\boldsymbol{\nu}_{-j}$ 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 Eqs. (3) in (2), the resulting expression can be referred to as Pair Copula Construction (PCC) and can be represented as a tree.[3] There are several classes of PCCs, the most general one is known as R-Vine copula.

3.2.1. R-Vine

An R-vine on n-elements is a nested set of $n-1$ trees,[4] $\mathscr{V}=(T_1,\ ...,T_i,\ ...,T_{n-1})$ with a set of edges E_i, and nodes $N_i=\{1,\ ...,n-i\}=E_{i-1}$. 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. $(\mathbf{F},\mathscr{V},B)$ is an R-vine copula specification as defined by Dissmann et al. (2013). $\mathbf{F}=(f(x_1),\ \cdots,f(x_n))$ is a vector of invertible distribution functions, $\mathscr{V}$ 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:

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

where $\mathbf{x}=(x_1,\ ...,x_n)$, 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. Likelihood based model selection methods fit the distribution in the "middle" and tails have little impact. This is a limitation of the AIC selection method. However, there is not perfect method for copula selection, and as Panagiotelis et al. (2012) and others have shown, it appears to be the best choice among alternative selection methods.
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.

$$\begin{aligned}\lambda_U&=\lim_{u\to1^-}P(X_1>F_1^{-1}(u)|X_2>F_2^{-1}(u))\\&=\lim_{u\to1^-}\frac{1-2u+C(u,u)}{1-u}\end{aligned} \tag{5}$$

$$\begin{aligned}\lambda_L&=\lim_{u\to0^+}P(X_1<F_1^{-1}(u)|X_2<F_2^{-1}(u))\\&=\lim_{u\to0^+}\frac{C(u,u)}{1-u}\end{aligned} \tag{6}$$

The estimation of Eqs. (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) $\widehat{C}(u,u)$, as defined in Deheuvels (1980):

$$\widehat{\lambda}_U=\lim_{i_U\to N^-}\frac{1-2\frac{i_U}{N}+\widehat{C}\left(\frac{i_U}{N},\frac{i_U}{N}\right)}{1-\frac{i_U}{N}} \tag{7}$$

$$\widehat{\lambda}_L=\lim_{i_L\to0^+}\frac{\widehat{C}\left(\frac{i_L}{N},\frac{i_L}{N}\right)}{1-\frac{i_L}{N}} \tag{8}$$

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 $\widehat{\lambda}_L(\cdot)$ and $\widehat{\lambda}_U(\cdot)$, 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 $\left(1-\frac{\alpha}{2}\right)100\%$ are also obtained from the same empirical distribution function.

[3] 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).

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

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):

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

$$\eta_{c,t} = \epsilon_{c,t}/\sqrt{h_{c,t}} \tag{10}$$

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

where $\text{r. ER}_{c,t} = \log(\text{r. ER}_{c,t}/\text{r. ER}_{c,t-1})$, $X_{c,t} = (\text{d. CDS}_{c,t},\ \text{r. Equity}_{c,t},\ \text{i. Diff}_{c,t})$ and $Z_t = (\text{r. SP500}_t,\ \text{r. VIX}_t)$. $\text{ER}_{c,t}$ is the exchange rate for country c in period t, $\text{d. CDS}_{c,t}$ is the first difference of the credit default swaps, $\text{r. Equity}_{c,t}$ is the stock index return, $\text{i. Diff}_{c,t}$ is the interest rate differential,[5] 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 rates. 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 on the behavior of commidity 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. Additionally, an important advantage of copula functions is that they measure both linear and nonlinear association between variables, while Pearson's correlation measures only linear association.

The R-Vine copula structure was identified according to the procedure described above. The selected R-Vine structure is shown in Fig. 2.

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

Next, the parameters of the selected copulas were estimated by maximum likelihood methods. The transformed observations to be used in the next trees were calculated using Eq. (1). Specification tests for the standardized residuals are presented in Tables 3 and 4. These steps (those for selection and those for estimation of the vine) were repeated using the transformed observations for all the remaining trees of the regular vine. The estimated parameters of the bivariate copulas of the R-Vine described in Fig. 2 are displayed in Table 5. 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 6. These coefficients are associated with the currency co-movements during large depreciations. None of these coefficients are statistically significant at conventional levels. This result indicates exchange rate co-movement does not depend on depreciation intensities. The lower tail dependence coefficients associated with large appreciations are presented in the bottom left panel of Table 6. 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 significantly more than during normal times. This result, that goes in line with those of Dimitriou and Kenourgios (2013) and Dimitriou et al. (2017), indicates that currency dependencies during times of extreme market movements are stronger than during times of market tranquility. 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.

Two different types of robustness tests were performed, one of country exclusion and the other of reduction of the sample period.

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

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

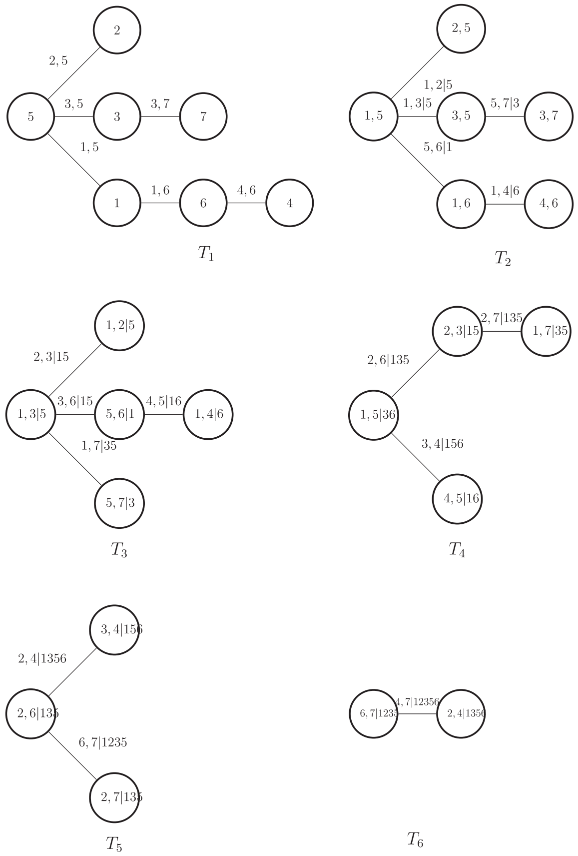

Fig. 2. Estimated regular vine. The numbers indicate the exchange rates of the 7 countries as follows: 1 = BRA, 2 = CHL, 3 = GER, 4 = INDN, 5 = S.AFR, 6 = S.KOR, 7 = UK.

Table 3
Univariate Specification tests for the standarized residuals.

	ARCH (LM) (lags = 45)	Portmanteau (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 4
Multivariate Specification tests for the standarized 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

Table 5
Regular Vine Specification.

	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	–

Table 6
Tail depedence 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	

Regarding the first, we excluded South Africa from the sample, and observed that results were qualitatively identical. Particularly, evidence of contagion was encountered only during periods of currency appreciation. With respect to the second, the sample period was shortened to exclude the Subprime financial crisis. Data was considered only for the period between 2009 and 2018. Results did not change as well.

Our findings are similar to those of other related studies, such as Loaiza-Maya et al. (2015a, 2015b). The asymmetric behavior 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 risk 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 et al. (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, Gomez-Gonzalez & Garcia-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 are likely to influence contagion in foreign exchange markets.

Large appreciations occurred in emerging markets, and also in many developed economies such as Germany and the United Kingdom, during our sample period as illustrated by Fig. 1. In fact, rapid and strong currency appreciations with respect to the United States Dollars were observed during the recent global financial crisis and in its aftermath. Various papers have found that spillovers from the Unites States markets to other international markets increased importantly during this time-period, mainly due to the implementation of quantitative easing schedules. For instance, Meegan, Corbet, and Larkin (2018) find evidence of significant idiosyncratic contagion transfer to a number of international financial markets, during each of the three respective quantitative easing programs, especially affecting foreign exchange markets. Higher than normal exchange rate co-movements in exchange rates observed during our sample period can be associated with the development of unconventional monetary policies in the United States and other developed economies during the international financial crisis as well.

Interestingly, contagion is more frequently observed in pairs of currencies including either the British Pound or the Euro. This result shows that the size and liquidity of exchange rate markets matter for contagion. Additionally, although it does not appear to be the most important factor, contagion has a geographical influence. In other words, it is more frequently observed within countries belonging to the same region (i.e., Chile and Brazil, the United Kingdom and Germany, and South Korea and Indonesia).

As expected, dependence is lower for Indonesia and South Korea, given peculiarities that make the behavior 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 and has an important regional component.

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 (Fratzscher, 2003) definition of contagion as increases in inter-dependence in times of extreme market movements.

All the estimated upper-tail dependence coefficients are statistically insignificant. This result indicates that currency co-movements during large depreciations are not significantly different than during normal times. On the contrary, most lower tail dependence coefficients, 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 importantly reduced during times of extreme currency appreciation. Exceptions are encountered in tail dependence coefficients including either Indonesia or South Korea. All of them are insignificant, except for the pair containing both countries.

We show that contagion is stronger for pairs of countries including either the United Kingdom or Germany. This finding illustrates the importance of market size and development for contagion. Additionally, contagion exhibits a regional component, being more probable between countries belonging to the same geographical region. This result sheds light for diversification of risk in global portfolios, especially during strong currency appreciations.

Our findings are similar to those of other related studies, such as Loaiza-Maya et al. (2015a, 2015b). The asymmetric behavior 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.

Our results show that diversification strategies using currencies from different countries must be time-variant. Particularly, they should be significantly different in times of distress than during normal times, as shown by Dimitriou and Kenourgios (2013) and Dimitriou et al. (2017).

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