Latin American Exchange Rate Dependencies: A Regular Vine Copula Approach

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LATIN AMERICAN EXCHANGE RATE DEPENDENCIES: A REGULAR VINE COPULA APPROACH*

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ABSTRACT. This study implements a regular vine copula methodology to evaluate the level of contagion among the exchange rates of six Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico and Peru) from June 2005 to April 2012. We measure contagion in terms of tail dependence coefficients, following Fratzscher's (1999) definition of contagion as interdependence. Our results indicate that these countries are divided into two blocs. The first bloc consists of Brazil, Colombia, Chile and Mexico, whose exchange rates exhibit the largest dependence coefficients, and the second bloc consists of Argentina and Peru, whose exchange rate dependence coefficients with other Latin American countries are low. We also found that most of the Latin American exchange rate pairs exhibit asymmetric behaviors characterized by non-significant upper tail dependence and significant lower tail dependence. These results imply that there exists contagion in Latin American exchange rates in periods of large appreciations, while there is no evidence of contagion during periods of currency depreciation. This empirical regularity may reflect the "fear of appreciation" in emerging economies identified by Levy-Yeyati, Sturzenegger, and Gluzmann [2013].

Keywords: Copula, Regular Vine, Exchange Rates, Tail Dependence Coefficients.

JEL Codes: C32, C51, E42.

1. INTRODUCTION

Since the seminal work of Meese and Rogoff [1983], empirical studies on exchange rates have mainly been focused on testing whether exchange rates are random walk processes, whereas less attention has been paid to the assessment of exchange rates co-movements. As shown in Kang, Wang, Yoon, and Yun [2002], Chadwick, Fazilet, and Tekatli [2012], Kuhl [2008], Orlov [2009], Benediktsdottir and Scotti [2009], Patton [2006], and Fernández [2007], exchange rates dependence is a relevant topic in economics because it is associated with several important topics, such

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as international economic policy coordination, economic policy assessment, risk hedging in financial exchange rate markets, the evaluation of monetary economic integration, financial market inefficiency testing and financial contagion assesment.

In this document, we are interested in studying the Latin American exchange rates level of contagion following Fratzscher's (1999) definition. He defines contagion as "the transmission of a crises to a country, that is caused by its proximity to the country where the crises originated", this definition interprets contagion as interdependence. Fratzscher [1999] also states that contagion is the single best indicator to predict currency crises. Therefore, measuring contagion is important to prevent or diminish the crises' effects by implementing suitable solutions such as global coordinated economic policy.

Studying the level of exchange rates market contagion gives information about how possible is that a currency crises spill over from one country to other countries. Following Benediktsdottir and Scotti [2009] and Patton [2006], we use copula functions to measure the exchange rates interdependencies.

The financial crisis of 2008 demonstrated the need to study in detail the performance of emerging markets such as the Latin American one. As the investors became aware of this crisis, emerging markets became an important destiny of investment. Nowadays, the European sovereign debt crisis made developed markets more vulnerable to uncertainty whereas some emerging countries exhibit more stable economic conditions and sustained economic growth. The relevance of emerging markets and especially the importance of the Latin American one ever since has increased, shedding light on the need to take into account the interdependencies of Latin American markets to make reliable and profitable portfolio decisions.

The aim of this paper is to evaluate the level of contagion in Latin American exchange rate market using a methodology that goes beyond the simple analysis of correlation breakdowns. Whether contagion differs in periods of large appreciations and large depreciations is also addressed. We use the tail dependence coefficients to measure of interdependence in both positive and negative extreme events. To model the multivariate dependence among the exchange rates, we use a pair copula construction approach with a regular vine copula specification. Regular vine structure is computed following Dissmann et al.'s (2012) methodology. The tail dependence coefficients were estimated according to Caillault and Guégan's (2005) technique.

Pair-Copula construction, initially proposed in the seminal work of Joe [1996] and extended by Bedford and Cooke [2001, 2002], is a method that allows one to compute a multivariate distribution as the product of $d(d-1)/2$ bivariate copulas. Studies such as Kurowicka and Cooke [2006] and Aas, Czado, Frigessi, and Bakken [2009] have implemented C-Vine and D-Vine pair-copula constructions. Although these methods use flexible structures to model dependence, they are restrictive in the sense that C-Vine and D-Vine are particular cases of regular vines.

This paper analyzes the exchange rates dependence of six Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico and Peru) over the period of June 22, 2005 to April 25, 2012. The results show that their exchange rate co-movement exhibits asymmetric behavior. There is significant co-movement in large appreciations whereas there is non-significant co-movements in large depreciations, indicating that there exists contagion in Latin American exchange rates in periods of large appreciations. This empirical regularity may be due to two different phenomena, which might reinforce each other. On the one hand, it may reflect the ”fear of floating” identified by G. and Reinhart [2002], which has been shown to be asymmetric in periods of currency appreciation and depreciation in emerging market economies. In fact, as Kocenda, Poghosyan, and Zemcik [2008], Pontines and R.S. [2011], and Levy-Yeyati, Sturzenegger, and Gluzmann [2013] show, emerging market economies are more sensitive to exchange rate appreciation than depreciation, and hence central banks are more likely to intervene foreign exchange markets in an attempt to depreciate their currencies. These ”synchronized” responses may generate a dependence effect in the behavior of exchange rates in emerging market economies.[1]

On the other hand, this interesting empirical result may reflect the fact that international investors' behavior appears to be different in moments of high global risk aversion and in periods of low global risk aversion (see, for instance, Fratzscher [2011], and Jeanneau and Micu [2012]). During times of high global risk aversion investors follow closer individual country fundamentals when making investment decisions on risky assets. Meanwhile, in periods of low global risk aversion and low interest rate levels in developed economies, international investors' decisions are less based on fundamentals and rely heavier on their search-for-yield appetite. As moments of low global risk aversion coincide with periods of currency appreciation in emerging markets, then it is more probable to observe exchange rate dependence in exchange rates in emerging markets during times of local currencies' appreciation.

Furthermore, the currencies of Brazil, Chile, Colombia and Mexico share the highest tail dependencies and the currencies of Peru and Argentina present the lowest ones. As expected, Argentina's Exchange rate behavior is quite independent from the behavior of other economies in the region, given particular issues related to the recent financial history of this country, as the process of debt restructuring that began in January 2005.

Meanwhile, in contrast to the other large economies in the region, Peru is financially dollarized. Therefore, international investors taking positions in Peruvian assets are less exposed to exchange rate risk, and therefore it is to expect that Peruvian currency's behavior is quite different from the behavior of other currencies in the region.

The manuscript is organized as follows. Section two explains the regular vine copula methodology. An empirical application for the Latin American exchange rates is shown in section three. Finally, in section four the concluding remarks are presented.

[1]Gómez-González and García-Suaza [2012] find evidence of an asymmetric momentum effect in emerging market economies Exchange rates, which is stronger during times of currency appreciation tan during periods of currency depreciation. Their findings go in line with ours.

2. Methodology

In this section, the R-Vine copula approach and some key concepts that are necessary to understand this technique are briefly explained. These definitions closely follow those of Dissmann, Brechmann, Czado, and Kurowicka [2012].

2.1. **Copula.** A $d-$variate copula $C(F(x_1),\ldots,F(x_d))$, is a cumulative distribution function whose marginals, $F(x_1),\ldots,F(x_d)$, are uniformly distributed on the unit interval.[2]

Following Sklar [1959], if $F_1(x_1),\ldots,F_d(x_d)$ are cumulative distribution functions of continuous random variables $x_1,\ldots,x_d$, then $C(F(x_1),\ldots,F(x_d))$ is a copula that represents the d-variate cumulative distribution function of $x_1,\ldots,x_d$.

$$F(x_1,\ldots,x_d)=C(F(x_1),\ldots,F(x_d)) \tag{1}$$

If $F_1(x_1),\ldots,F_d(x_d)$ are continuous functions, then $C(F(x_1),\ldots,F(x_d))$ exists and is unique. Equation (1) shows that a multivariate distribution function has information on dependence and information about its marginals. The copula function C models the dependence structure.

2.2. **Pair-Copula Decomposition.** The Pair-Copula constructions method (hereafter PCCs) was proposed in the seminal work of Joe [1996] and extended by Bedford and Cooke [2001, 2002]. The PCCs definition is given below.

A density function $f(x_1,\ldots,x_d)$ can be factorized as:

$$f(x_1,\ldots,x_d)=f(x_d)\;f(x_{d-1}|x_d)\ldots f(x_1|x_2,\ldots,x_d) \tag{2}$$

Any of the marginal distributions in the right hand of (2) can be written as:

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

In which $\boldsymbol{\nu}=\{x_{i+1},\ldots,x_d\}$ is the conditioning set of the marginal distribution of x_i, ν_j is a variable of the set $\boldsymbol{\nu}$, $\boldsymbol{\nu}_{-j}$ are the remaining variables in $\boldsymbol{\nu}$ after extracting ν_j, $i=\{1,\ldots,(d-1)\}$ and $c(u_1,u_2)$ is the density copula defined as $\frac{\partial C(u_1,u_2)}{\partial u_1 \partial u_2}$.

When (3) is iteratively decomposed, $f(x_i|\boldsymbol{\nu})$ becomes the product of bivariate density copulas and the marginal density function of x_i. If all the marginal distributions in (2) are decomposed iteratively as in (3), $f(x_1,\ldots,x_d)$ results in the product of bivariate density copulas and the marginal densities of $x_1,\ldots,x_d$. The former result is referred to as a pair copula construction of $f(x_1,\ldots,x_d)$.

There are several PCCs, depending on the selection of ν_j. Two special PCCs of $f(x_1,\ldots,x_d)$ are C-Vine and D-Vine, whose densities are as follows:

C-Vine

$$f(x_1,\ldots,x_d)=\prod_{k=1}^{d} f_k(x_k)\prod_{j=1}^{d-1}\prod_{i=1}^{d-j} c_{j,j+i|1,\ldots,j-1}\left(F_{j|1,\ldots,j-1}\left(x_j|x_{1,\ldots,j-1}\right),F_{j+i|1,\ldots,j-1}(x_{j+i}|x_{1,\ldots,j-1})\right)$$

[2] A detailed revision of copulas can be found in Nelsen [2006], Joe [1997], Becerra and Melo [2008], among others.

D-Vine

$$f(x_1,\ldots,x_d)=\prod_{k=1}^{d} f_k(x_k)\prod_{j=1}^{d-1}\prod_{i=1}^{d-j} c_{i,i+j|i+1,\ldots,i+j-1}\left(F_{i|i+1,\ldots,i+j-1}\left(x_i|x_{i+1,\ldots,i+j-1}\right),F_{i+j|i+1,\ldots,i+j-1}(x_{i+j}|x_{i+1,\ldots,i+j-1})\right)$$

These vine structures can be easily understood as graphs.[3] For this purpose, it is necessary to define the following concepts.

Tree definition. *If N is a set of nodes and E is a set of edges, then a tree is a graph $T=(N,E)$ that is connected and has no cycles.*

An example of a tree with five nodes is presented in Figure 1.

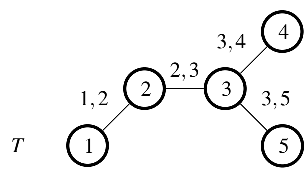

FIGURE 1. Tree example. $N=\{1,2,3,4,5\}$, $E=\{\{1,2\},\{2,3\},\{3,4\},\{3,5\}\}$

Vine definition. *$V=(T_1,\ldots,T_{d-1})$ is a vine on d elements if:*

(i) T_1 is a tree with nodes $N_1=\{1,\ldots,d\}$ and a set of edges denoted E_1

(ii) For $i=2,\ldots,d-1$, T_i is a tree with nodes $N_i=E_{i-1}$ and edge set E_i.

Therefore, a vine is a nested set of trees in which the edges of tree i are the nodes of tree $i+1$. Examples of C-Vine and D-Vine specifications are displayed in Figures 2 and 3.

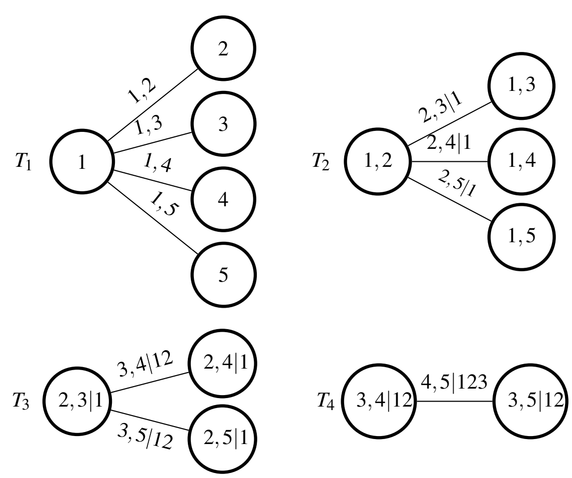

FIGURE 2. C-Vine with 5 variables.

[3]Vines are a tool from graph theory. In the context of pair copula constructions, they are useful for finding a correct decomposition of the joint density.

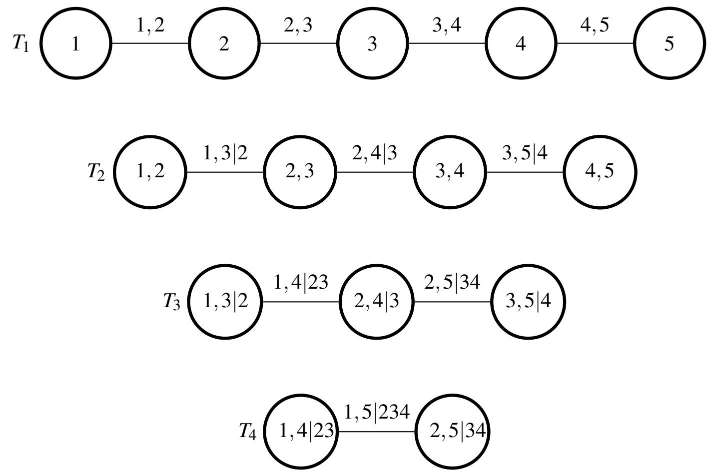

FIGURE 3. D-Vine with 5 variables

The edges in Figures 2 and 3 indicate bivariate copulas in the C-Vine and D-Vine densities for five variables.

2.3. **Regular vines and regular vine copula.** C-Vines and D-Vines are particular cases of a general set of decompositions named regular vines. Some theoretical definitions about regular vines and the automated regular vine selection and estimation technique developed by Dissmann, Brechmann, Czado, and Kurowicka [2012] are presented in this section.

Regular Vine definition (R-Vine). *$\mathcal{V} = (T_1, \ldots, T_{d-1})$ is an R-vine on d elements if:*

(i) *T_1 is a tree with nodes $N_1 = (1, \ldots, d)$ and a set of edges denoted E_1*
(ii) *T_i is a tree with nodes $N_i = E_{i-1}$ and edges E_i, for $i \in (2, \ldots, d-1)$*
(iii) *For $i \in (2, \ldots, d-1)$ and $\{a, b\} \in E_i$ with $a = \{a_1, a_2\}$ and $b = \{b_1, b_2\}$ it must hold that $\#(a \cap b) = 1$.*

Therefore, an R-Vine is a nested set of trees in which the edges in tree i are the nodes in tree $i+1$. The third condition, named the proximity condition, ensures that two nodes are connected in tree $i+1$ if they were edges connected to a common node in the tree i. Some set concepts that are important in the R-Vine graph framework are defined next.

Complete union, conditioning and conditioned sets definitions. *The complete union of an edge $e_i \in E_i$ is the set $U_{e_i} = \{n \in N_1 | \exists e_j \in E_j, j = 1, \ldots, i-1, \text{ with } n \in e_1 \in e_2 \in \cdots \in e_{i-1} \in e_i\} \subset N_1$. For $e_i = a, b \in E_i$, $a, b \in E_{i-1}$, $i = 1, \ldots, n-1$, the conditioning set of an edge e_i is $D_{e_i} = U_a \cap U_b$ and the conditioned sets of an edge e_i are $C_{e_i,a} = U_a \backslash D_{e_i}, C_{e_i,b} = U_b \backslash D_{e_i}$ and $C_{e_i} = C_{e_i,a} \cup C_{e_i,b} = U_a \triangle U_b$, in which $A \triangle B := (A \backslash B) \cup (B \backslash A)$ denotes the symmetric difference of two sets.*

Constraint set definition. *The constraint set for $\mathcal{V}$ is the set:*

$$C\mathcal{V} = \{(\{C_{e_i,a}, C_{e_i,b}\}, D_{e_i}) | e \in E_i, e = \{a, b\}, i = 1, \ldots, d-1\}$$

Based on the example in Figure 4, the complete union, conditioning, conditioned and other sets used in the R-Vine density expression are computed in Table 1.

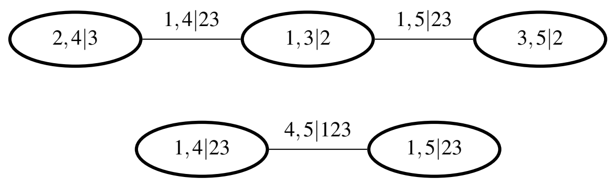

FIGURE 4. Edge example

Edge: $e = \{4,5\|123\} = \{C_{e,a}, C_{e,b}\|D_e\}$	
$a = \{\{2,4\|3\},\{1,3\|2\}\}$	$b = \{\{1,3\|2\},\{3,5\|2\}\}$
$a_1 = \{2,4\|3\}$, $a_2 = \{1,3\|2\}$	$b_1 = \{1,3\|2\}$, $b_2 = \{3,5\|2\}$
$U_a = \{1,2,3,4\}$	$U_b = \{1,2,3,5\}$
$D_e = U_a \cap U_b = \{1,2,3,4\} \cap \{1,2,3,5\} = \{1,2,3\}$	
$C_{e,a} = U_a \backslash D_e = \{1,2,3,4\} \backslash \{1,2,3\} = \{4\}$	
$C_{e,b} = U_b \backslash D_e = \{1,2,3,5\} \backslash \{1,2,3\} = \{5\}$	

TABLE 1. Complete union, conditioning and conditioned sets of the edge $\{4,5|123\}$ of Figure 4

An example of the first tree of an R-Vine specification is presented in Figure 5. As shown, this specification is more general than D-Vine and C-Vine structures.

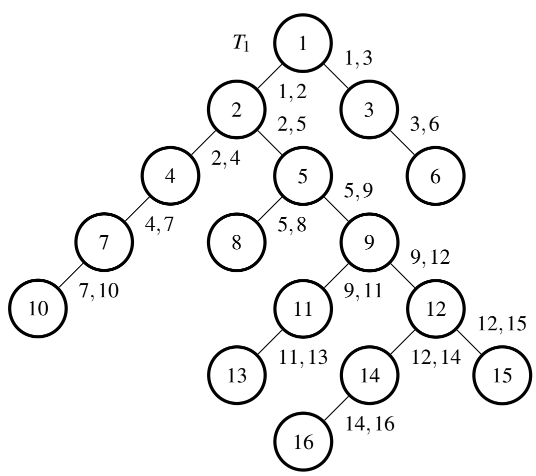

FIGURE 5. First tree of an R-Vine with 5 variables

Regular Vine Copula definition. *$(\boldsymbol{F},\boldsymbol{V},\boldsymbol{B})$ is an R-Vine copula specification if $\boldsymbol{F}=(F_1,\ldots,F_d)$ is a vector of continuous invertible marginal distributions functions, $\boldsymbol{V}$ is a $d-$dimensional R-Vine and $\boldsymbol{B}=\{B_e|i=1,\ldots,d-1;e\in E_i\}$ is a set of bivariate copulas related to a set of edges of $d-1$ trees.*

As shown in Dissmann, Brechmann, Czado, and Kurowicka [2012], there is a unique density for an R-Vine copula specification as follows:

$$f_{1,\ldots,d}(x)=\prod_{k=1}^{d}f_k(x_k)\prod_{i=1}^{d-1}\prod_{e\in E_i}c_{C_{e,a},C_{e,b}|D_e}(F_{C_{e,a}|D_e}(x_{C_{e,a}}|x_{D_e}),F_{C_{e,b}|D_e}(x_{C_{e,b}}|x_{D_e})) \quad (4)$$

$$F_{C_{e,a}|D_e}(x_{C_{e,a}}|x_{D_e})=\frac{\partial C_{C_a|D_a}(F_{C_{a,a1}|D_a}(x_{C_{a,a1}}|x_{D_a}),F_{C_{a,a2}|D_a}(x_{Ca,a2}|x_{D_a}))}{\partial F_{C_{a,a1}|D_a}(x_{C_{a,a1}}|x_{D_a})} \quad (5)$$

$$=h(F_{C_{a,a1}|D_a}(x_{C_{a,a1}}|x_{D_a}),F_{C_{a,a2}|D_a}(x_{Ca,a2}|x_{D_a})) \quad (6)$$

Equation 5 is known as the h function and it is used to compute the arguments of the copulas in equation 4 in the case of conditional distributions.

Dissmann [2010] and Dissmann, Brechmann, Czado, and Kurowicka [2012] employ a matrix representation of a regular vine to compute the likelihood and simulation of a regular vine copula. The constraint set of a regular vine in matrix framework is written as follows.

Matrix Constraint set definition. *Let $M=(m_{i,j})_{i,j=1,\ldots,d}$ be a lower triangular matrix. The i-th constraint set for M is*

$$C_M(i)=\{(\{m_{i,i},m_{k,i}\},D)|k=i+1,\ldots,d,\ D=\{m_{k+1,i},\ldots,m_{d,i}\}\}$$

for $i=1,\ldots,d-1$. D is set to $\emptyset$ if $k=d$. The constraint set for matrix M is the union $CM=CM(1)\cup\ldots\cup CM(d-1)$. For the elements of the constraint set $(\{m_{i,i},m_{k,i}\},D)\in CM$, $\{m_{i,i},m_{k,i}\}$ is called the conditioned set and D the conditioning set.

Given the matrix constraint set definition, the density function in equation (4) can be written as:

$$f_{1,\ldots,d}(x)=\prod_{j=1}^{d}f_j(x_j)\prod_{k=d-1}^{1}\prod_{i=d}^{k+1}c_{m_{k,k},m_{i,k}|m_{i+1,k},\ldots,m_{d,k}}\left(F_{m_{k,k}|m_{i+1,k},\ldots,m_{d,k}}(z_1(k,i)),F_{m_{i,k}|m_{i+1,k},\ldots,m_{d,k}}(z_2(k,i))\right)$$
$$z_1(k,i)=x_{m_{k,k}|m_{i+1,k},\ldots,m_{d,k}}$$
$$z_2(k,i)=x_{m_{i,k}|m_{i+1,k},\ldots,m_{d,k}}$$

2.4. **R-Vine Specification.** Some relevant concepts about R-vine copulas have been discussed in the previous sections. Nevertheless, as indicated in Morales-Napoles [2010], there are $\frac{d!}{2}2^{\binom{d-2}{2}}$ R-Vine structures for a d-dimensional exercise. As a result, it is important to consider a method that selects a suitable vine structure. Dissmann, Brechmann, Czado, and Kurowicka [2012] suggest the following sequential procedure to identify and estimate an R-Vine structure.

(i) The tree structure is selected by maximizing the sum of the absolute empirical Kendall correlation coefficients using the algorithm proposed in Prim [1957].
(ii) The pair-copula families associated with the tree specified in the previous step are chosen by minimizing the AIC.
(iii) The parameters of the selected copulas are estimated by maximum likelihood methods.
(iv) The transformed observations that will be used in the next tree are calculated using equation (5).
(v) Steps (i) to (iv) are repeated using the transformed observations for all of the remaining trees of the regular vine.

2.5. **Tail Dependence coefficients.** The tail dependence coefficients (TDC) indicate the probability that one variable exceeds a high (low) threshold given that the other variable exceeds a high (low) threshold. Therefore, the tail dependence coefficients show how two random variables depend on one another in extreme events. The definitions of upper and lower tail dependence are as follows:

$$\lambda_U = \lim_{u\to 1^-} P\left(X_1 > F_1^{-1}(u) \mid X_2 > F_2^{-1}(u)\right) = \lim_{u\to 1^-} \frac{1-2u+C(u,u)}{1-u} \tag{7}$$

$$\lambda_L = \lim_{u\to 0^+} P\left(X_1 < F_1^{-1}(u) \mid X_2 < F_2^{-1}(u)\right) = \lim_{u\to 0^+} \frac{C(u,u)}{u} \tag{8}$$

Given (7) and (8), the estimation of the tail dependence coefficients requires the calculation of a parametric copula. However, the tail dependence coefficients for every possible pair of variables are difficult to estimate in a regular vine copula. In this context, non-parametric TDC estimators can be obtained as follows:

$$\widehat{\lambda}_U = \lim_{i_U\to N^-} \frac{1-2\frac{i_U}{N}+\hat{C}(\frac{i_U}{N},\frac{i_U}{N})}{1-\frac{i_U}{N}} \tag{9}$$

$$\widehat{\lambda}_L = \lim_{i_L\to 0^+} \frac{\hat{C}(\frac{i_L}{N},\frac{i_L}{N})}{\frac{i_L}{N}} \tag{10}$$

in which $\widehat{C}(\frac{i_1}{N},\frac{i_2}{N}) = \frac{1}{N}\sum_{j=1}^{N} \mathbf{1}_{(F(x_{1,j})\leq \frac{i_1}{N}, F(x_{2,j})<\frac{i_2}{N})}$ is the empirical copula. i_U and i_L are associated with the thresholds used in the estimation of the non-parametric TDC.

The upper and lower TDC and their confidence intervals in a regular vine copula approach are obtained for all pair-copulas through a simulation exercise as follows:

(i) Given the estimated regular vine, N simulations of a d-dimensional vector are obtained using the algorithms proposed in Dissmann, Brechmann, Czado, and Kurowicka [2012]. This exercise is replicated S times.
(ii) The lower and upper tail dependence coefficients for thresholds i_U and i_L, TDC_s are estimated for each replication s using equations (9) and (10).
(iii) The upper and lower TDC are selected as the mean of the estimated TDC_s.
(iv) The $(1-\alpha/2)100\%$ confidence intervals for the upper and lower TDC are selected as the corresponding quantiles of their empirical distribution.

3. Empirical Application

The empirical analysis is based on the exchange rates of six Latin American countries: Argentina, Brazil, Chile, Colombia, Mexico and Peru, over the period of 22 June 2005 to 25 April 2012. The first differences of the logarithms of exchange rates are graphed in Figure A.1 of Appendix A.

This method is performed in three steps. In the first step, the marginal distributions are modeled. Next, the R-Vine copula is estimated using the pseudo-sample associated with the standardized residuals of the models of the first step. Finally, the tail dependence coefficients are computed.

3.1. **Models for the Marginal Distributions.** Initially, the first and second moments of the variables are modeled using an ARX(p)-GARCH(1,1) specification as follows:

$$r.ER_{c,t} = \alpha_{c,0} + \sum_{i=1}^{p_c} \alpha_{c,i}\, r.ER_{c,t-i} + \sum_{j=1}^{q_c} \boldsymbol{\beta}'_{c,j}\, \boldsymbol{X}_{c,t-j} + \sum_{j=1}^{q_c} \boldsymbol{\gamma}'_{c,j}\, \boldsymbol{Z}_{t-j} + \varepsilon_{c,t} \tag{11}$$

$$\eta_{c,t} = \varepsilon_{c,t}/\sqrt{h_{c,t}} \tag{12}$$

$$h_{c,t} = \omega_{c,0} + \omega_{c,1} h_{c,t-1} + \omega_{c,2}\varepsilon^2_{c,t-1}, \tag{13}$$

in which $r.ER_{c,t} = log(ER_{c,t}/ER_{c,t-1}), \boldsymbol{X}_{c,t} = (i.Diff_{c,t}, r.Equity_{c,t}, d.CDs_{c,t})'$, $\boldsymbol{Z}_t = (r.S\&P500_t, r.VIX_t)'$, $ER_{c,t}$ is the exchange rate level of country c in period t, $i.Diff_{c,t}$ is the interest rate differential, $r.Equity_{c,t}$ is the stock index return, $d.CDs_{c,t}$ is the first difference of the credit default swaps, $r.S\&P500_t$ is the U.S. stock index return, $r.VIX_t$ is the VIX return, $c = \{ARG, BRA, CHI, COL, MEX, PER\}$ and $\eta_{c,t} \overset{iid}{\sim} (0,1)$.

Dornbusch [1976] and Frenkel [1976] provide a rationale for the link between the exchange rate and interest rate differentials. The former presents a model of exchange rate overshooting due to sluggish price adjustment, while the later introduces a model in which prices are flexible and stresses the link between the expected depreciation of a currency and expected inflation differentials. Both models assume that the uncovered interest rate parity holds. Recent empirical papers have extended this framework assuming an exchange risk premium, which is approximated by using control variables similar to those included in this document (see, for instance, Kanas [2005] and S. and R. [2009]).

The standardized residuals and some specification tests are presented in Figure B.1 and Tables B.1 and B.2 of Appendix B, respectively. The results of these tests show no evidence of misspecification.

Finally, the estimated pseudo-sample ($u_{c,t} \equiv F_c(\eta_{c,t})$) was obtained as the empirical distribution of the standardized residuals. The estimated pseudo-sample is used as an argument of the Regular-Vine copula.

3.2. **Specification of the regular vine copula.** The R-Vine copula structure was identified according to the methodologies described in section 2.4. The selected R-Vine structure is shown in Figure 6.

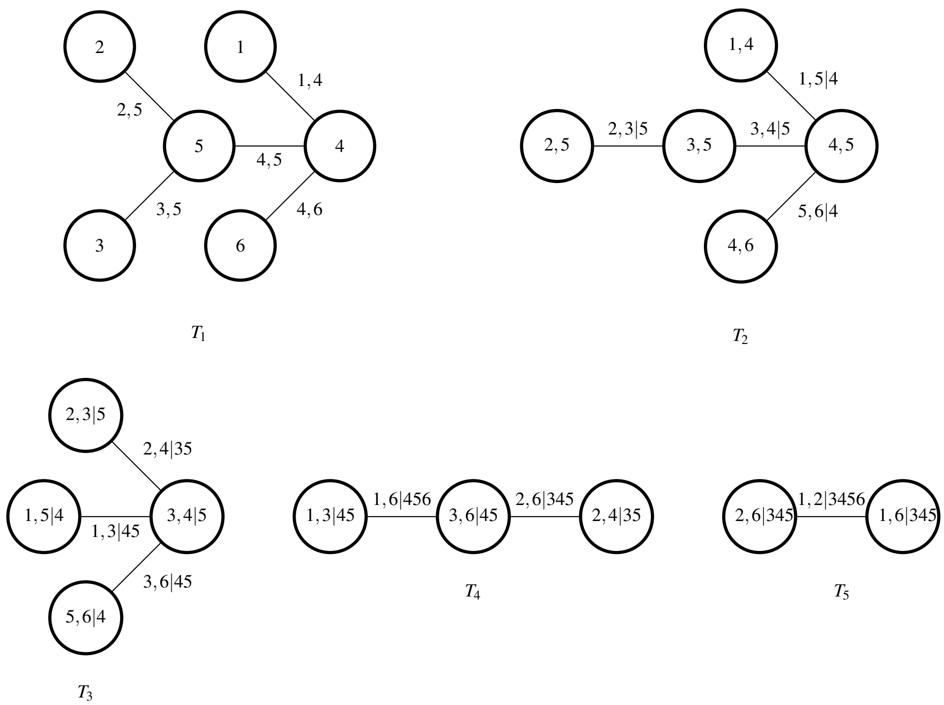

FIGURE 6. Estimated regular vine. The numbers indicate the exchange rates of the 6 Latin American countries as follows: 1=ARG, 2=BRA, 3=CHI, 4=COL, 5=MEX, 6=PER

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 Joe-Clayton, 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.

The estimated parameters of the bivariate copulas of the R-Vine described in Figure 6 are displayed in Table 2. Most of the parameters of the conditional and unconditional pair-copulas are significant. Those parameters that are non-significant are restricted to some copulas that include either Argentina or Peru.

	Pair-Copula	Parameter 1	Parameter 2	Std 1	Std 2
ARG_BRA	Gaussian	0.020	-	0.033	-
ARG_CHI	t	-0.031	10.103	0.037	3.745
ARG_COL	t	0.091	9.430	0.037	3.271
ARG_MEX	t	0.044	6.891	0.038	1.978
ARG_PER	Rotated Joe 270 degrees	-1.041	-	0.028	-
BRA_CHI	Survival Gumbel	1.103	-	0.025	-
BRA_COL	Survival Gumbel	1.108	-	0.025	-
BRA_MEX	t	0.394	6.802	0.030	1.714
BRA_PER	Clayton	0.043	-	0.037	-
CHI_COL	t	0.160	5.940	0.037	1.376
CHI_MEX	t	0.355	3.864	0.034	0.608
CHI_PER	t	-0.076	9.617	0.037	3.520
COL_MEX	t	0.282	4.346	0.036	0.771
COL_PER	t	0.182	7.823	0.036	2.323
MEX_PER	t	0.094	11.259	0.036	4.048

TABLE 2. Regular vine copula estimation results.

Based on the estimated regular vine copula, the tail dependence coefficients were obtained using the simulation procedure explained in section 2.5. This exercise includes $S = 500$ simulations of $N = 10000$ observations of a $6-$dimensional vector. The TDC were calculated for the thresholds $i^*_L/N = 0.01$ and $i^*_U/N = 0.99$.

	ARG	BRA	CHI	COL	MEX	PER
ARG		0.070	0.087	0.087	0.100	0.060
BRA	0.039*		0.106	0.100	0.180	0.063
CHI	0.055*	0.180*		0.159	0.223*	0.076
COL	0.056*	0.182*	0.154*		0.181	0.100
MEX	0.073*	0.175*	0.220*	0.171*		0.091
PER	0.024	0.058*	0.054*	0.088*	0.076*	

TABLE 3. Tail dependence coefficients. Numbers above (below) the diagonal are associated with upper (lower) tail dependence. The symbol (*) indicates that the estimated coefficient is significant at the 5% level.

The upper tail dependence coefficients of the six Latin American exchange rates are displayed in the top right panel of Table 3. These coefficients are associated with the currencies co-movement in large depreciations. These results show that the only significant tail dependence in depreciation, at the 5% significance level, is between the Chilean peso and the Mexican peso; any other pairwise relationship is not significant.

On the other hand, the lower tail dependence coefficients associated with large appreciations are presented in the bottom left panel of Table 3. By contrast with the upper tail case, they are all significant at the 5% significance level. The dependence between the Argentine peso and the Peruvian nuevo sol is the only exception. This indicates that the currencies are significantly correlated in large appreciations. Furthermore, the highest lower tail dependencies are obtained among Brazil, Chile, Colombia and Mexico.

The previous results indicate that there are asymmetric co-movements in the 6 Latin American exchange rates. However, there are two exceptions: the Chilean peso and the Mexican peso which have tail correlations that indicate a significant symmetric dependency of 0.22 and the Argentine peso and the Peruvian nuevo sol which exhibit neither upper nor lower significant tail dependence. All of the remaining Latin American exchange rate pairs show asymmetric behavior characterized by non-significant upper tail dependence and significant lower tail dependence. These results imply that the probability that Latin American exchange rates move together against the dollar in periods of large appreciation is higher than the probability that they move together in periods of high depreciation. Therefore, the Latin American exchange rates present significant level of contagion in periods of large appreciation and a non-significant level of contagion in periods of large depreciation.

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 risks 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 appreciation given the "fear of appreciation" encountered by Levy-Yeyati, Sturzenegger, and Gluzmann [2013], among other studies. Thus, more dependence is observed among emerging markets exchange rates during periods of local currency appreciation.

As expected, dependence is lower for Argentina and Peru, given peculiarities that make the behavior of their exchange rates different from those of the other large Latin American economies. Particularly, Argentina's debt restructuring program, which began in January 2005, and the fact that Peru is the only financially dollarized economy in the group of large Latin American countries.

Our results shed light for international investors interested in taking positions is Latin American securities. They show that diversification investing in different Latin American economies is easier during times of currency depreciation than during times of appreciation. However, diversification is also possible when appreciation is observed whenever securities from Argentina or Peru are considered by international investors.

3.3. **Robust analysis.** Two additional exercises were performed to evaluate the robustness of the results. The first one uses a sample 22 ranging form June 2005 to 21 April 2009 and the second one uses a sample ranging from 22 April 2009 to 25 April 2012. A comparison of the lower and upper tail dependence coefficients for these two samples and the total sample are presented in Tables 4 and 5 and in Figures C.1 and C.2 of Appendix C.

	Jun-22-2005 to Apr-21-2009	Apr-22-2009 to Apr-25-2012	Jun-22-2005 to Apr-25-2012
ARG_BRA	0.045*	0.006	0.039*
ARG_CHI	0.051*	0.029	0.055*
ARG_COL	0.097*	0.036*	0.056*
ARG_MEX	0.014	0.027*	0.073*
ARG_PER	0.077*	0.020	0.024
BRA_CHI	0.154*	0.180*	0.180*
BRA_COL	0.170*	0.260*	0.182*
BRA_MEX	0.078*	0.171*	0.175*
BRA_PER	0.052*	0.081*	0.058*
CHI_COL	0.125*	0.223*	0.154*
CHI_MEX	0.117*	0.301*	0.220*
CHI_PER	0.042*	0.083*	0.054*
COL_MEX	0.254*	0.238*	0.171*
COL_PER	0.023	0.220*	0.088*
MEX_PER	0.019	0.143*	0.076*

TABLE 4. Lower tail dependence coefficients for three samples. The symbol (*) indicates that the estimated parameter is significant at the 5% level.

The results for the three samples indicate that there are no significant differences in the tail dependence estimations. Only three out of the 30 upper tail coefficients are different at the 5% level of significance: Colombia-Peru, Chile-Mexico and Brazil-Mexico.

	Jun-22-2005 to Apr-21-2009	Apr-22-2009 to Apr-25-2012	Jun-22-2005 to Apr-25-2012
ARG_BRA	0.068	0.058	0.070
ARG_CHI	0.075	0.064	0.087
ARG_COL	0.060	0.079	0.087
ARG_MEX	0.075	0.064	0.100
ARG_PER	0.060	0.057	0.060
BRA_CHI	0.154	0.068	0.106
BRA_COL	0.080	0.074	0.100
BRA_MEX	0.094	0.176	0.180
BRA_PER	0.081	0.056	0.063
CHI_COL	0.109	0.062	0.159
CHI_MEX	0.122	0.074	0.223*
CHI_PER	0.074	0.053	0.076
COL_MEX	0.084	0.066	0.181
COL_PER	0.063	0.066	0.100
MEX_PER	0.060	0.057	0.091

TABLE 5. Upper tail dependence coefficients for three samples. The symbol (*) indicates that the estimated parameter is significant at the 5% level.

4. CONCLUDING REMARKS

This study implements a regular vine copula methodology to evaluate the level of contagion among the exchange rates of six Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico and Peru) from June 2005 to April 2012. We measure contagion in terms of tail dependence coefficients, following Fratzscher's (1999) definition of contagion as interdependence.

Most of the estimated upper tail dependence coefficients of the six Latin American exchange rates show no significant results. This indicates that there are not significant currency co-movements in large depreciations. On the other hand, almost every lower tail dependence coefficient, associated with large appreciations, is significant at the 5% significance level. Consequently, the currencies are significantly correlated in large appreciations.

The lower tail dependence coefficients show that there are two blocs of countries. The first bloc consists of Brazil, Colombia, Chile and Mexico. The exchange rates of these countries have the highest dependence coefficients among them. The second bloc consists of Argentina and Peru. The Argentine and Peruvian exchange rates have low dependence coefficients with the other Latin American currencies.

The previous results indicate that the countries' exchange rates show asymmetric behavior characterized by non-significant upper tail dependence and significant lower tail dependence. These results imply that the probability that Latin American exchange rates move together against dollar in periods of large appreciation is higher than the probability that they move together in periods of high depreciation. Therefore, there exists contagion in Latin American exchange rates in periods of large appreciations. This result is related to the asymmetric behavior of both emerging market central banks and international investors taking positions in emerging markets' assets during episodes of currency appreciation and depreciation. Firstly, the literature on the push and pull factors behind portfolio investments has shown that investors are less worried about individual countries' fundamentals during times of low global risk aversion, associated with periods of emerging markets currency appreciation. Hence, exchange rate dependence is more likely to be observed during episodes of local currency appreciation. Secondly, recent findings in the literature on the "fear of floating" have shown that central banks in emerging economies respond aggressively when local currency appreciation occurs, while they tend to intervene less when local currency depreciation is observed. This second fact may also explain a higher dependence of Latin American countries' exchange rate during periods of currency appreciation.

Finally, our results shed some light on possible diversification strategies that can be followed by international investors. The fact that there is no exchange rate dependence during moments of local currencies' depreciation illustrates that exchange risk diversification can be achieved when taking position in assets of different Latin American economies during these periods of time. In episodes of Latin American currencies' appreciation exchange rate risk diversification is also possible, but options to diversify this risk are somehow more limited. Particularly, exchange rate risk will be better diversified if positions on Peruvian and Argentinean assets are undertaken whenever positions in assets from any other of the big Latin American economies are undertaken.

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APPENDIX A. EXCHANGE RATES GRAPHS

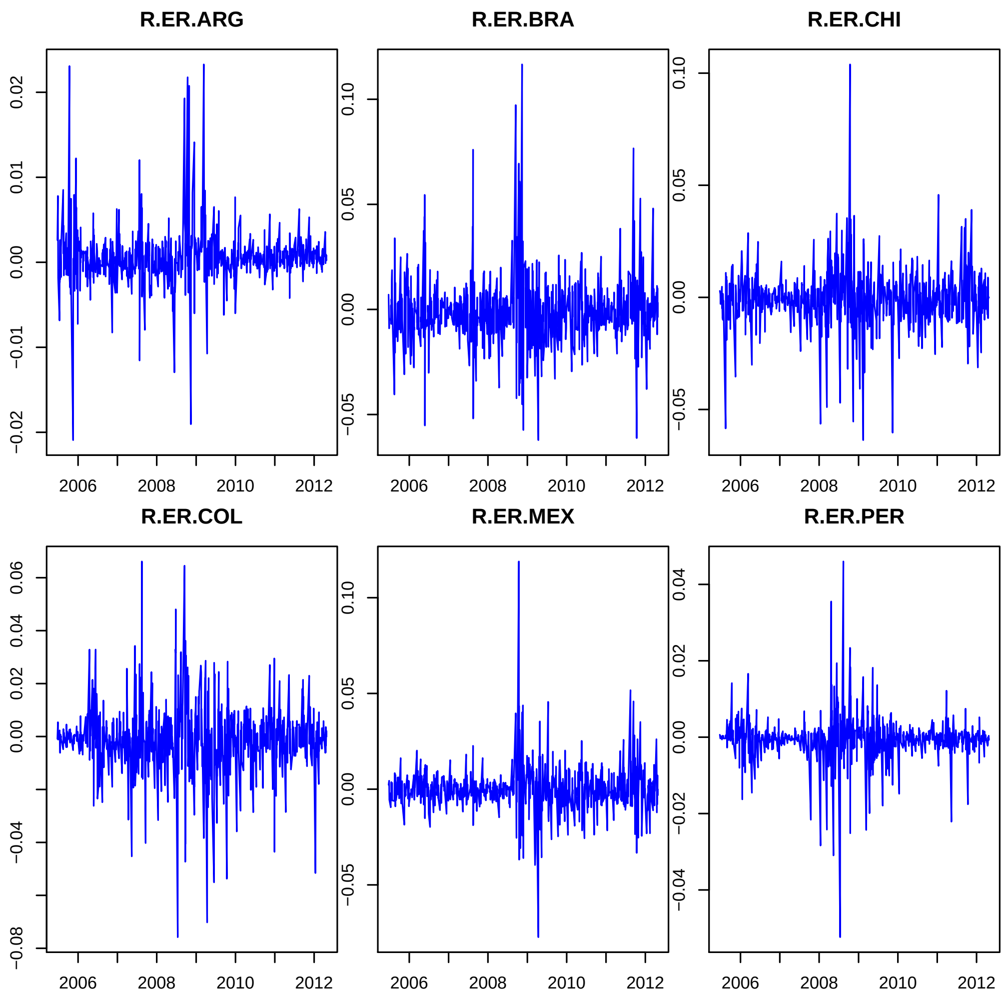

FIGURE A.1. First difference of the logarithm of exchanges rates of Argentina, Brazil, Chile, Colombia, Mexico and Peru

APPENDIX B. RESIDUALS AND DIAGNOSTIC TESTS

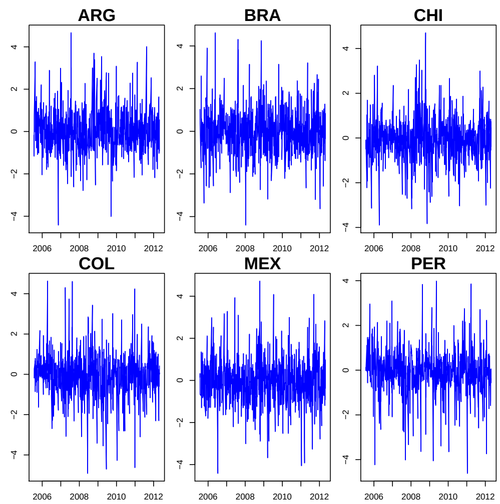

FIGURE B.1. Standardized residuals of the marginal models

	ARCH (LM) (lags = 12)	Portmanteau (lags = 100)
ARG	0.888	0.564
BRA	0.942	0.610
CHI	0.475	0.799
COL	0.378	0.215
MEX	0.258	0.284
PER	0.019	0.739

TABLE B.1. Univariate specification tests for the standardized residuals (P-Values)

	Null Hypothesis	Lags	Statistic	P-Value
Breusch and Godfrey (LM)	No autocorrelation	4	163.169	0.131
Portmanteau	No autocorrelation	100	3533.78	0.522
LM (squared residuals)	No MGARCH effect	12	445.358	0.318

TABLE B.2. Multivariate specification tests for the standardized residuals

Appendix C. Tail dependence coefficients for different samples

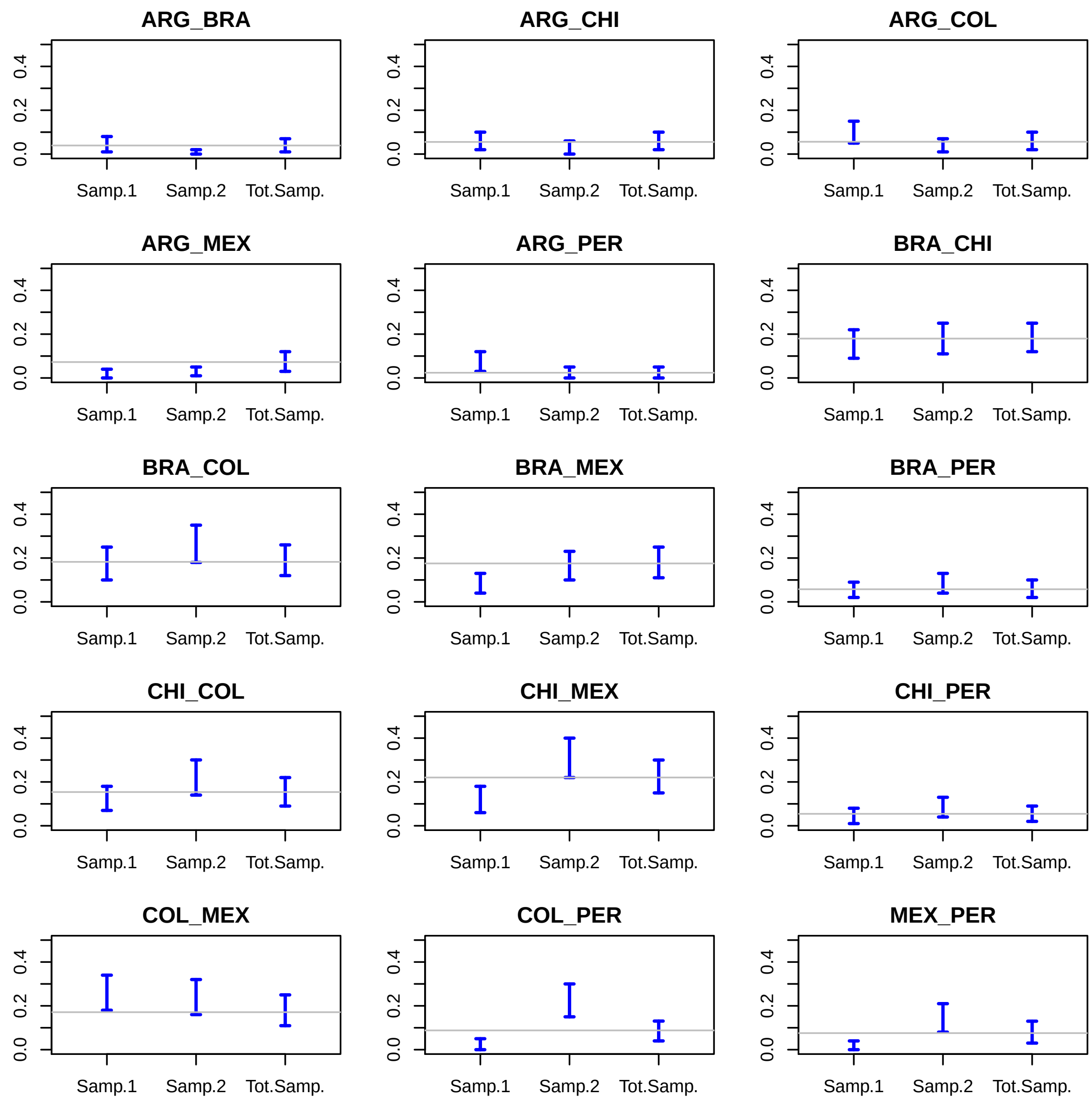

Figure C.1. Lower tail dependence 95% confidence intervals for three samples. Sample 1: Jun-22-2005 to Apr-21-2009, Sample 2: Apr-22-2009 to Apr-25-2012 and Total Sample: Jun-22-2005 to Apr-25-2012.

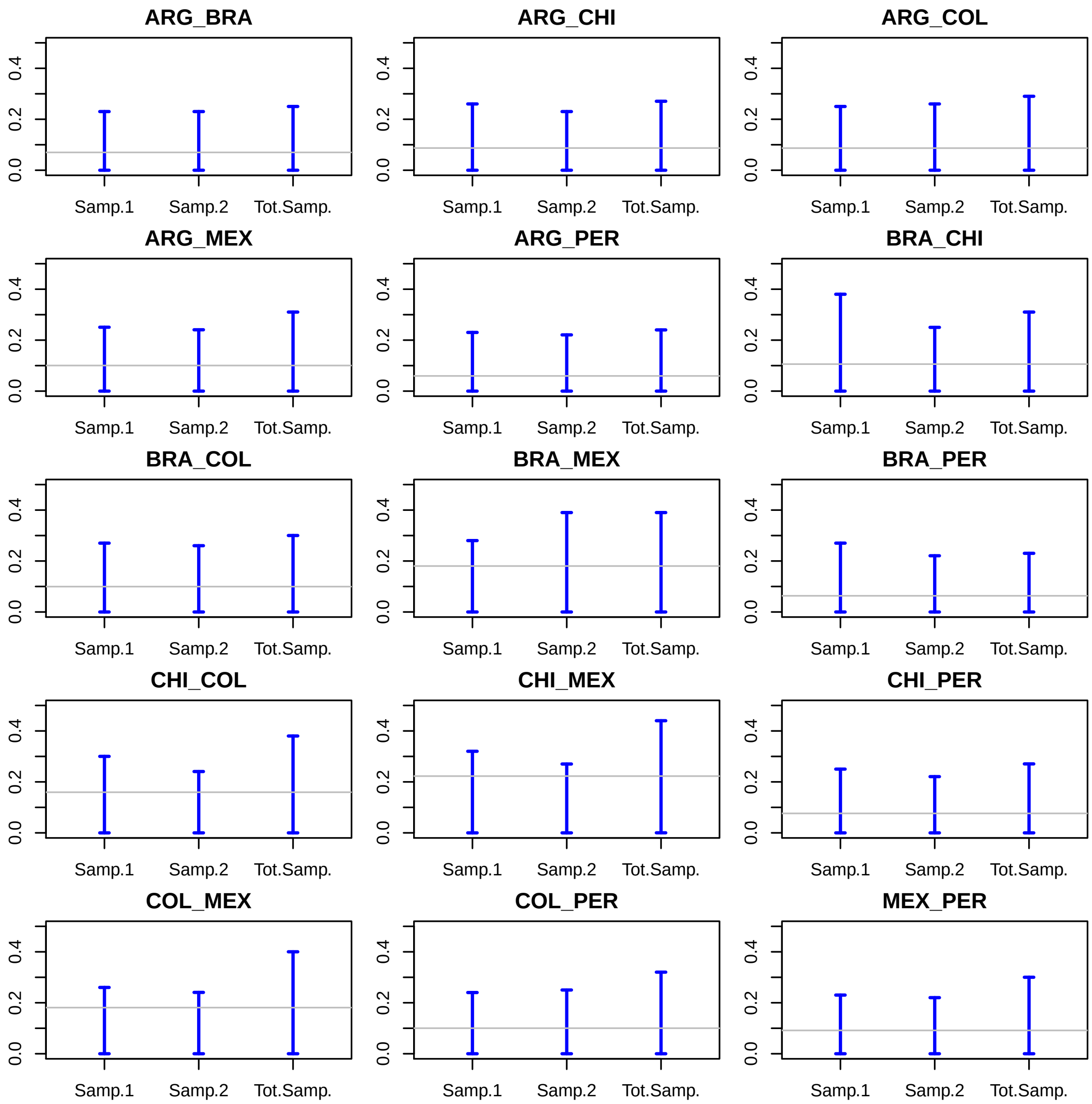

FIGURE C.2. Upper tail dependence 95% confidence intervals for different samples. Sample 1: Jun-22-2005 to Apr-21-2009, Sample 2: Apr-22-2009 to Apr-25-2012 and Total Sample: Jun-22-2005 to Apr-25-2012.