MEASURING CO-DEPENDENCIES OF ECONOMIC POLICY UNCERTAINTY IN LATIN AMERICAN COUNTRIES USING VINE COPULAS

Abstract

We analyze the dependence structure of economic policy uncertainty in four Latin American economies (Brazil, Chile, Colombia, Mexico) using vine copula modeling with various forms of tail dependence. Our results suggest that there are significant dependencies in economic uncertainty among the economies considered and that tail dependence is more prevalent in the period preceding the Global Financial Crisis and becomes less relevant in the post-crisis period. Previous works suggest that uncertainty in economic activity can have substantial effects on economic issues ranging from business cycles to contagion effects of financial crises. Correspondingly, our results have significant implications on the analysis of macroeconomic activity and contagion of financial crises, especially for emerging economies.

JEL Classifications: C22, D80, N16

Keywords: Economic policy uncertainty, vine copula, emerging economies

Highlights

- A vine copula model is used to analyze dependencies of Economic Policy Uncertainty (EPU) between four Latin American economies (Brazil, Chile, Colombia, Mexico).
- The results suggest significant dependencies and co-movement.
- There is evidence of upper tail dependence, mostly concentrated in the period before the Global Financial Crisis.
- Results suggest that contagion of uncertainty was significant before 2008 but became less important after 2008.

1 Introduction

For many years emerging market economies have been subject to large swings in business cycles, financial market returns and macroeconomic fundamentals. During the years 1998-2002, most Latin American countries experienced economic turmoil and sluggish growth rates. **A vast literature establishes that during the same period contagion of crises was significant in Latin American countries and mostly propagated through financial market linkages (Calvo (1999) and Reinhart *&* Calvo (1996)).**

Following this period, the years 2003-2007 marked a period of remarkable growth and stability, mainly due to favorable commodity prices and credit conditions, international trade, and remittances. However, when the global financial crisis (henceforth GFC) hit markets, Latin American countries were among the hardest hit in the emerging world in terms of sluggish growth and per capita GDP as compared to the boom years (Stiglitz (2010); Ocampo (2009)). Countries such as Colombia and Mexico witnessed the slowdown during the first half of the 2008, whereas, in other countries, especially Brazil, growth came to a halt in September 2008. Although measures taken by the Chilean authorities such as auctioning foreign currency denominated deposits to national banks, swap lines, and the flexibilization of reserve requirements helped to preserve stable conditions in the domestic economy (Chan-Lau (2010)) in the initial phase of the crisis, the Chilean economy experienced similar sluggish growth during 2009.

The similarity of the experience of Latin American economies is no surprise; previous research such as Basnet *&* Sharma (2013) suggests that these economies exhibit synchronous business cycle characteristics both in the short run and in the long run, whereas Basnet *&* Sharma (2015) show that these economies have both long term common trends and short term common cycles in their exchange rates.

In connection with the similar experience of these economies a large body of research recently established that domestic and external uncertainty shocks can influence economic fundamentals such as output, inflation and the interest rate as well as financial markets. In their analysis of G7 and BRIC countries Guo *et al.* (2018) show that economics policy uncertainty (henceforth EPU) and stock market returns exhibit asymmetric dependency whereas Cerda *et al.* (2016) show that EPU affects the real economy in Chile in the short run and in the long run.

An implication of these studies is that EPU can be understood as an underlying mechanism that affects movements in real and financial variables in emerging economies in general and Latin American economies in particular.

Building on these connections, we contribute to the nascent literature by analyzing the dependence structure of EPU for four Latin American countries Brazil, Chile, Colombia and Mexico) using time-constant Regular Vines (R-vines). Copula models are increasingly used to analyze interdependence of financial variables, especially when non-Gaussian distributions are considered (see Aas (2016) for a survey of financial applications of copula models). Following previous studies such as Patton (2006), Boero *et al.* (2011); and Min *&* Czado (2014) that investigate exchange rate dependencies using copulas, we uncover the dependence structure of EPU of the countries that we analyze and also investigate tail dependencies between the measures. To the best of our knowledge, this is the first study to use vine copula to analyze dependence between uncertainty in Latin American countries.

Using the EPU measure (introduced by Baker *et al.* (2016)), which is based on news coverage of economic issues in respective countries, we analyze EPU linkages for the period 1996-2018. To explore possible differences after the GFC, we analyze the pre-GFC and post-GFC periods and the full sample period. Our findings indicate that there are indeed strong correlations between the EPU indexes considered and that there are upper tail dependencies, mostly in the pre-GFC period, implying contagion effects of uncertainty during crisis periods.

We also find that symmetric tail dependencies are not present in our period of analysis.

With the help of a study of this kind we extend the debate on the 2008 GFC using vine copula by examining the policy uncertainty co-dependencies among the sample nations. The present work is divided into five sections: the following section provides an overview of the methodology featuring R-vines, section 3 describes the data, section 4 presents the results, and section 5 concludes.

2 Methodology

2.1 Copula and Vine-copula

Copula and other models

An important topic that has gained relevance since the GFC is the need for appropriate models to capture complex dependence structures of several variables and accurately assess risk. In one of the early contributions, Mandelbrot (1963) documented that asset returns exhibit fat tails and don't necessarily follow Gaussian distributions. It is possible to explore such dependence using non-Gaussian models with the availability of large samples of multivariate data.

While multivariate DCC GARCH models of Engle & Sheppard (2001) and Engle (2002) have been used for such purposes, they use covariances for dependence modeling among time series, while maintaining positive definite covariance matrices. Such issues related to separation of marginal times series modeled with univariate GARCH models and dependence structure are addressed by copula modeling (Brechmann & Czado (2013)).

This model is based on the theorem by Sklar (1959), which allows for constructing general multivariate distributions from copulas and marginal distributions. **Earlier forms of copulas were bivariate in nature (parametric and non-parametric) but the issue of complexity arises while modeling more than two dimensions. This was resolved by Joe (1997) with the formulation of multivariate dimension based on pair-wise copulas and Bedford & Cooke (2001) using graphical measures to decompose multivariate copulas to bivariate pair-copulas. When compared to bivariate copula structures, vine copula models offer greater flexibility as shown in Fischer *et al.* (2009).**

There are several advantages of copula models over other models: 1) copula functions are robust techniques as they are able to separate the dependence structure from the choice of margins (da Silva Filho *et al.* (2012)); 2) can capture non-linear dependencies (Shi *et al.* (2017)); 3) are invariant to increasing and continuous transformations (Ning (2010)); 4) help to analyze the dependencies when the returns are non-normal (Jondeau & Rockinger (2006)) and 5) don't necessitate the conditional quantiles to be linear as with models such as quantile regressions (see Bernard & Czado (2015) for shortcomings of the quantile regression approach).

Finally, an important advantage of copula models over other dependency models is that while other models typically don't allow for asymmetric tail dependencies, copula models allow for upper, lower, symmetric and asymmetric tail dependencies. Hence, they qualify for the analysis of dependency between a large class of assets and indexes.

Copula theory

Sklar (1959) introduced the copula concept, which describes the dependence structure between variables. **Copulas can be described as functions that connect multivariate distribution with any given univariate marginal distribution functions.** Thus, copula modeling is one of the few methods that allows for greater flexibility in analyzing multivariate and marginal distributions.

The copula functions are technically assumed to have a vector of Z random variables with marginal distribution functions of $F_i(Z_i)$ where $i = 1, 2, \ldots, p$. Given a set of transformation $V_i = F_i(Z_i)$ comprising uniformly distributed and dependent vector of random variables $V = (V_1, \ldots, V_p)$ on $[0, 1]^p$. If the functions of $F_i(Z_i)$ are continuous then the joint distribution function of Z is assumed as:

$$F(z) = C(F_1(z_i), \ldots, F_n(z_p)) = C(V_1, \ldots, V_p) \tag{1}$$

where $C(V)$ is expressed as the copula of the distribution, $C : [0, 1]^p \rightarrow [0, 1]$ and $V = (V_1, \ldots, V_p)$. The copula C can be related to a joint distribution function with vector V. Equation 1 is Sklar's theorem and can be extended using the copula distribution $C(V)$ as:

$$C(v) = F(F_1^{-1}(v_1), \ldots, F_p^{-1}(v_n)) \tag{2}$$

While the associated copula density can be presented as:

$$c(v) = \frac{\partial^p C(V_1, \ldots, U_p)}{\partial(V_1, \ldots, V_p)} \tag{3}$$

Lebrun & Dutfoy (2009*b*) explain that the joint probability density function of Z, which is $f_Z(z_p) = f_z(z_1, \ldots, z_p)$ can be expressed as:

$$f_z(z_1, \ldots, z_p) = c\{F_1(z_1), \ldots, F_p(z)\} \prod_{i=1}^{p} f(z_1) \tag{4}$$

where $f_i(z_i)$ denotes the marginal probability density function of z_i. Equation (4) joins the copula density functions and the marginal distributions comprising all relevant information about the dependence structure of the random variables. Joe (1997) and Lebrun & Dutfoy (2009*a*) compute the conditional marginal distributions of the vector of Z random variables as:

$$F_{i|1,\ldots,j-1}(z_i|z_i, \ldots, z_{i-1}) = C_{i|1,\ldots i-1}(v_i|v_i, \ldots, v_{i-1}) \tag{5}$$

where

$$C_{i|1,\ldots,i-1}(v_i|v_i, \ldots, v_{i-1}) = \frac{\frac{\partial^{i-1} C(V_1,\ldots,V_i,1,\ldots,1)}{\partial(V_1,\ldots,V_{i-1})}}{\frac{\partial^{i-1} C(V_1,\ldots,V_i,V_{i-1},1,\ldots,1)}{\partial(V_1,\ldots,V_{i-1})}} \tag{6}$$

Considering a bivariate case, equation (6) with $v_1 = u$ and $v_2 = u$ can be represented as:

$$F_{Z2|Z1}(z_2|z_1) = C(u|v) = \frac{\partial C(v, u)}{\partial v} \tag{7}$$

Vine-Copulas

Vines are graphical structures which embody joint probability distributions whereas copulas are the combined distribution of two or more random variables. A vine copula is based on pair copula construction (PCC) method which includes the construction of multivariate combined distribution from bivariate and conditional bivariate copulas. Additionally, Aas *et al.* (2009) lay out that the pair-copula construction (PCC) principle can be used with arbitrary pair-copulas, referred to as the graphical structure of R-vines. Furthermore, Dissmann *et al.* (2013) developed an automated algorithm of jointly searching for appropriate R-vines tree structures, the pair-copula families and their parameters.

Along with pioneering pair-copula modeling Bedford *&* Cooke (2002) also introduced so-called canonical (C-vines) and drawable vines (D-vines). These models were later extended by Aas *et al.* (2009) who employed non-Gaussian pair copula modeling such as the bivariate Student-t copula, bivariate Clayton copula, and bivariate Gumbel copula. C-vines exhibit star shape structures having a tree sequence, whereas, D-vines possess path structures, i.e., any particular node is not associated to more than two different nodes. For a technical description of pair-copula construction, we refer the reader to Aas *et al.* (2009).

Earlier versions of pair-copulas were criticized because of their inability to solve complicated models. Later, regular vine copulas (R-Vine) employing diagram algorithms as a possible way to solve the complicated models were developed. R-Vines emerged as a methodological advancement over the former because of their flexible nature as they involve the specification of arbitrary bivariate copulas, and have the potential ability to model a wide range of complicated dependencies. However, the greatest shortcoming of R-vines is the presence of the curse of dimensionality. Therefore, the computational effort needed to evaluate the model increases exponentially with the dimension.

Brechmann (2010) discusses the use of simplified truncated modeling techniques to mitigate the problem of curse of dimensionality. For instance, Allen *et al.* (2017) advise truncation of a regular vine at level M where independent copulas replace any pair-copulas that are either equal to or larger than M. These independent copulas are known as Gaussian copulas, which are easier in specification among other variants of copulas and are simpler in their interpretation of the correlation parameter.

2.2 Estimation

Marginal distributions Models

Sklar (1959) mentions two important components of a multivariate distribution function: (i) the marginal distributions that represents the specific features of each series, and (ii) a copula which comprehensively indicates the dependencies among the series. Therefore, we apply the model due to Bollerslev (1986) Generalized autoregressive conditional heteroskedasticity (GARCH) (p, q) for the characterization of the marginal densities of the returns series (s_t) before estimating the copulas, which is represented as follows:

$s_t = \phi + \mu_t$

$\delta_t^2 = \psi + \sum_{j=1}^{q} \beta_j \mu_{t-j}^2 + \sum_{i=1}^{p} \gamma_i \delta_{t-i}^2$

where ϕ is the expected return of the series and μ_t indicates the random disturbance term with zero mean white noise process following the Student-t distribution:

$\sqrt{\frac{d}{\delta_t^2(d-2)}}\epsilon_t \ \mathrm{iid} t_d$

where d denotes the degrees of freedom and δ_t^2 is the conditional variance of ϵ_t which is represented as:

$\delta_t^2 = \psi + \sum_{i=1}^{p} \beta_i \epsilon_{t-p}^2 + \sum_{j=1}^{q} \gamma_j \delta_{t-i}^2$

where ψ is the intercept, ϵ_{t-p} denotes the ARCH term and δ^2_{t-i} the GARCH term. Akaike Information Criteria (AIC) selects the appropriate number of lags (p, q). Then, we employ a two-step maximum likelihood approach: in the first step, we estimate the parameters of the marginal distributions using maximum likelihood approach and in the second step, we maximize the log-likelihood function by introducing the probability transformation of the standardized marginal residuals as pseudo-sample observations for the copula function.

3 Data

We use EPU index data (in log differences) for four major Latin American countries, Mexico, Brazil, Chile and Colombia as compiled by Baker *et al.* (2016). The index is based on news coverage frequency of policy-related economic issues and serves as a proxy for economic uncertainty. There are many uncertainty measures such as the VIX for developed countries. In contrast, uncertainty measures are scant for emerging economies and the EPU index provides a scaled measure of the appearance of uncertainty in news surrounding economic issues. The data spans the period from January 1996 to May 2018. The advantage of using monthly data is that extreme co-movement within the sample period is expected more frequently and potential tail dependencies can be captured more accurately. We also believe that the movements in the economic policy uncertainty indexes among the nations can reflect the situation of the intra economic and market conditions to a large extent. We divide our period of analysis into the pre-GFC (January 1996–December 2008), post-GFC (January 2009–December 2018) periods, and the full sample baseline period (January 1996-December 2018).

4 Results

In our analysis we used R, C and D vine copulas for the purpose of comparison. The use of C-Vines is appropriate when there are pivotal elements within the selection, i.e. when the dependence structure of the other variables is measured with respect to the pivotal variable. The pivotal variable is the one that maximizes the sum of Kendall's tau, i.e. pairwise dependencies. R-Vines on the other hand are less restrictive and don't necessarily need pivotal elements.

We find that R-vine performs best based on AIC and SIC. Palaro *&* Hotta (2006) in their study select the copula based on AIC criterion as it provides the best fit and tends to be superior in small samples (McQuarrie *&* Tsai (1998)). In the present study, we use both criterions to select the appropriate copula that provides the best fit. Consequently, we reported results for R-vine in the main text while for robustness purposes we report C-vine results in the appendix[1].

In the following, we present the results for the R-Vine copula for the periods under consideration: pre-GFC, post-GFC and full sample.

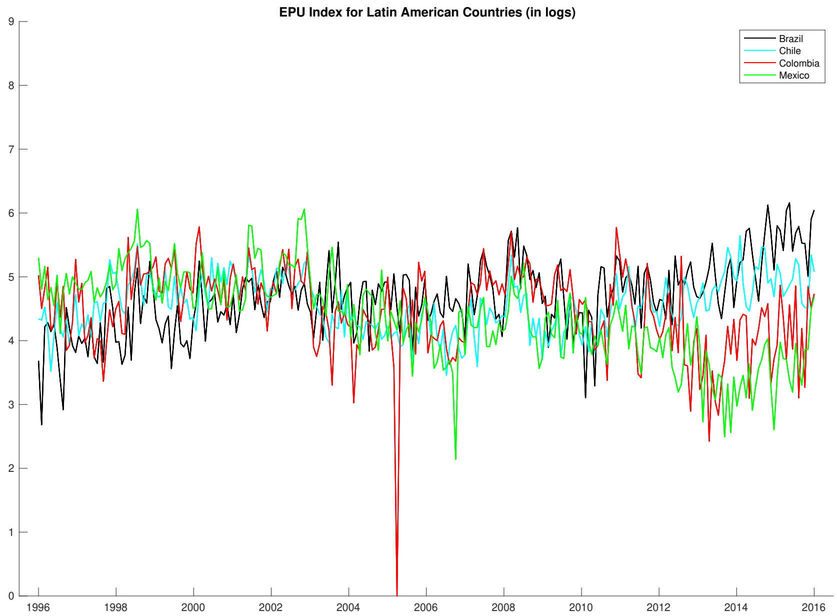
4.1 R-Vine Copulas

We present the results of the dependence structure of the EPU indexes of the four different nations using the R-Vine co-dependency model. These models help with tracing the dependencies between uncertainty indexes which plays a vital role in the underpinning of economies trade cycles. To consider the possibility of tail dependencies, we allow for six copula families ; Gaussian/Normal copula, Student t copula, Clayton copula, Gumbel copula, Frank copula and Joe copula. Details on the characteristics of these copula families can be found in Joe (2014). In summary, Gaussian and Frank copula don't exhibit tail dependencies, Gumbel and Joe copula exhibit upper tail dependencies and Clayton copula

[1]Further results of D vine are available upon request.

exhibit lower tail dependencies. The t copula stands out as it exhibits both upper and lower tail dependency.

Figure 1: EPU Index (in logs)



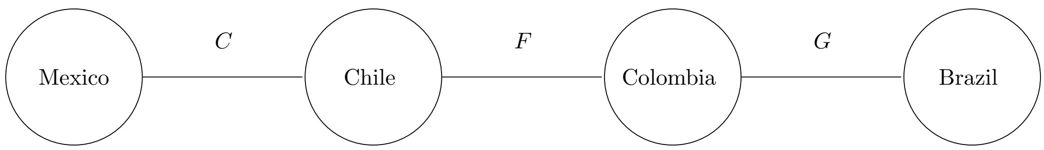
The time series data of the four countries EPU indexes are presented in figure 1. We divide the analysis into three sub-periods covering the pre-GFC, the post-GFC, and the full sample periods and further document the results of the three sub sample analysis in section 4.

R-Vine: Pre-GFC Period

Most Latin America economies recorded substantial economic growth between 2003 and 2007. Past studies discuss four important factors held responsible for this boom: growing international trade (9.3% per year between 2003–06), a significant increase in commodity prices, high levels of remittances, and remarkable financing conditions (Ocampo (2009)). In the following, we present the tree structure for the pre-GFC period using the R-Vine copula.

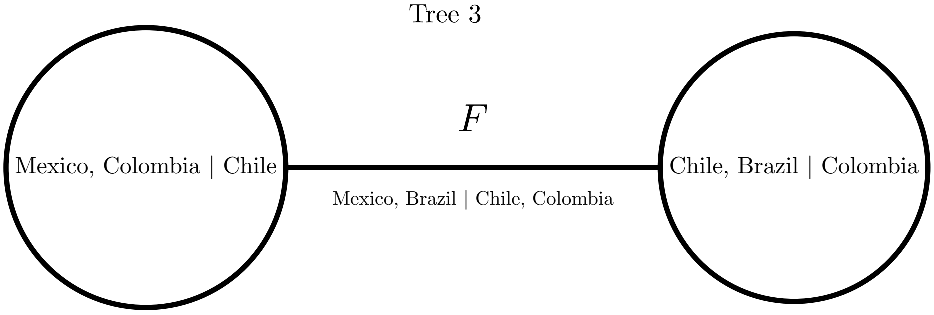
Figure 2: Results R-Vine Tree-1, 2 and 3, Pre-GFC

Tree 1



Tree 2

Tree 3



It is evident from figure 2 that the R-Vine structure is more flexible as compared to the C-Vine structure. We find that the EPU indexes of all the countries are associated to one another, except Brazil and Mexico which can also be seen in tree 2 and tree 3. Therefore, as a pair the EPU indexes of Brazil, Columbia and Chile have the strongest co-dependency and on the other hand the EPU indexes of Mexico, Chile and Columbia also have strongest co-dependency among one another.

In table 1, we present the structure matrix, which represents the graphical trees as displayed in figure 2 in form of a lower triangular matrix. This method of storing the information contained in R-vine trees in form of a lower triangular matrix was proposed by Dissmann *et al.* (2013) and allows for an efficient matrix representation for the evaluation of conditional distributions of R-vine copula. Denoting the countries that we consider with the codes BR = Brazil, CL = Chile, CO = Colombia and MX = Mexico, the first column represents the information in tree 3 which connects the two nodes: that Brazil and Mexico are the conditioned indexes whereas Chile and Colombia are the conditioning indexes. Column 2 includes the information in tree 3, column 3 the information in three 2 etc.

In table 2 we present the specification matrix which shows which type of copula family captures the bivariate dependency structure of the different indexes that we use. We employ AIC to select the appropriate copula which delivers the "best fit" for every pair of variables from the following: 1 = Gaussian/Normal copula, 2 = Student t copula (t-copula), 3 = Clayton copula, 4 = Gumbel copula and survival Gumbel Copula, 5 = Frank copula, 6 = Joe copula. The AIC adjusts the log likelihood of a copula for the number of estimated parameters (Dissmann *et al.* (2013)). **Using this nomenclature, the entry "5" that is given for Brazil and Chile denotes that a Gumbel copula with upper tail dependency is appropriate to represent the dependency between the two countries' respective indexes.**

It is clear from the table that different dependencies conditioned across the same node employ three different copulas. In this case, with reference to the first column, the first copula used is the Frank copula (no 5), followed by Gumbel copula (no 4) and Joe copula (no 6). In columns 2 and 3, we can see that the remaining relationships are best characterized by Clayton, Gumbel and Frank copula families. These results imply that upper tail dependencies are the most

relevant form of tail dependency in the pre-GFC period within the group that we consider.

The implication of these results is that in the pre-GFC period, dependency between the countries' respective indexes is more prevalent during periods of heightened uncertainty such as crises than during normal times. This result supports earlier work such as Valdés (2000) that suggest that contagion is stronger for negative shocks to creditworthiness in Latin American economies in the pre-GFC period.

Table 1: R-Vine Copula Structure Matrix

$$\begin{bmatrix} BR & 0 & 0 & 0 \\ MX & CO & 0 & 0 \\ CL & MX & CL & 0 \\ CO & CL & MX & MX \end{bmatrix}$$

BR = Brazil, CL = Chile, CO = Colombia and MX = Mexico

Table 2: R-Vine Copula Specification Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	5	0	0	0
Colombia	4	3	0	0
Mexico	6	4	5	0

1 = Gaussian/Normal copula, 2 = Student t copula (t-copula), 3 = Clayton copula, 4 = Gumbel copula and survival Gumbel Copula, 5 = Frank copula, 6 = Joe copula

Table 3: R-Vine Copula Tau Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	-0.169	0	0	0
Colombia	0.021	0.089	0	0
Mexico	0.138	0.331	0.347	0

We report the tau matrix for the pre-GFC period using R-Vines in table 3. The entries in the bottom of the row indicate the positive and strongest co-dependencies among the countries EPU indexes. We also find a positive coefficient of the tau for rest of the diagonals except for the country combination Brazil and Chile. This implies that a positive or negative changes in the economic policy uncertainty of Brazil would bring negative or positive changes in the policy uncertainty of Chile respectively. We document the strongest and positive dependencies between Colombia and Mexico as compared to any other countries combinations. Further, the weakest positive dependency is found for the countries Brazil and Colombia.

R-Vine: Post-GFC Period

We now focus our attention to the post-GFC period. It is apparent from figure 3 that the trees have changed considerably as compared to the pre-GFC period. It is evident from tree 1 that Brazil is now linked to Colombia through Chile and Mexico, while during the pre-GFC period, Brazil was linked to Mexico via Colombia and Chile (see figure 3).

Figure 3: Results R-Vine Tree-1, 2 and 3, Post-GFC

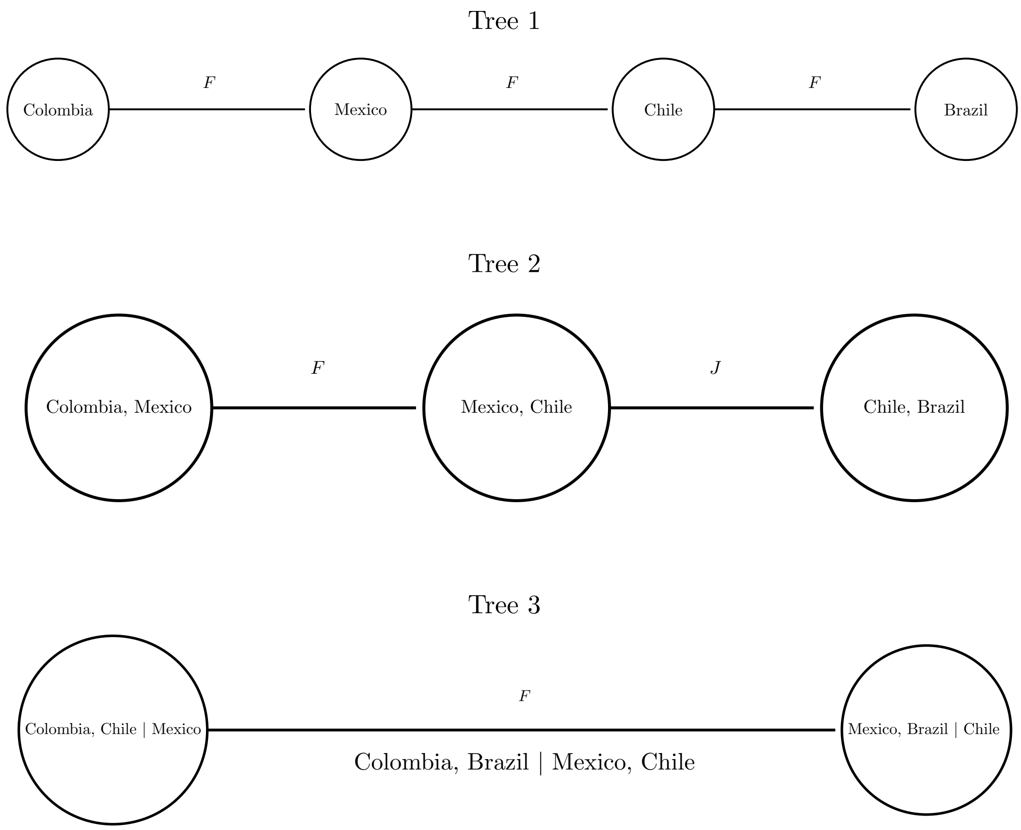


Table 4: R-Vine Copula Structure Matrix

$$\begin{bmatrix} BR & 0 & 0 & 0 \\ CO & CL & 0 & 0 \\ MX & CO & CO & 0 \\ CL & MX & MX & MX \end{bmatrix}$$

BR = Brazil, CL = Chile, CO = Colombia and MX = Mexico

Table 5: R-Vine Copula Specification Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	5	0	0	0
Colombia	5	6	0	0
Mexico	5	5	5	0

1 = Gaussian/Normal copula, 2 = Student t copula (t-copula), 3 = Clayton copula, 4 = Gumbel copula and survival Gumbel Copula, 5 = Frank copula, 6 = Joe copula

Table 6: R-Vine Copula Tau matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	0.133	0	0	0
Colombia	-0.069	0.061	0	0
Mexico	0.304	-0.147	0.398	0

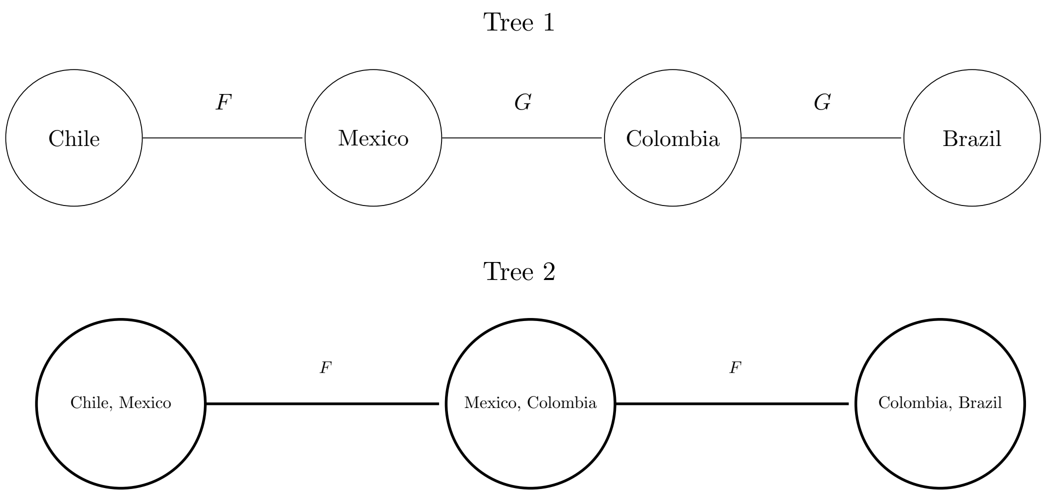
Table 5 shows the type of copulas used to map the co-dependencies among the EPU indexes. We find that the Frank copula dominates with five entries while the Joe copula appears only once. These results confirm that in the post-GFC period tail dependencies became less relevant. **This is likely a reflection of the change in the policy environment and increased resilience in Latin American economies in the post-GFC period. While these economies had different idiosyncratic experiences in the post-GFC period, they were relatively resilient to the adverse effects of the crisis, especially when compared to the 1990's as argued by Didier *et al.* (2012). The same authors argue that this is likely due to the fact that like most other emerging economies, Latin American economies lacked the proper policy tools to tackle external shocks before the crisis but shifted towards better policies in the post-GFC period.**

The tau matrix is presented in table 6 and reveals that the dependencies between the countries have significantly changed during the post-GFC period. Interestingly, there are now two negative entries, specifically for the country combinations Chile and Mexico and Brazil and Colombia for the post-GFC period. We also find that the strongest and positive dependency is exhibited by the combination Colombia and Mexico while the weakest relationship is exhibited by Chile and Colombia. **These results are in line with EPU movements after 2008 as can be seen in figure 1: when compared to their pre-GFC levels, the EPU indexes of Brazil and Chile steadily increased post-GFC while the indexes of Colombia and Mexico were lower.**

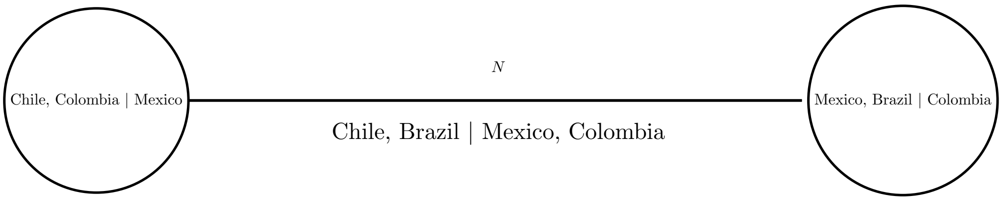
R-Vine: Full Sample Period

The trees of the vine copula for the full sample period are presented in figure 4.

Figure 4: Results R-Vine Tree-1, 2 and 3, Full Sample Period



Tree 3



The trees exhibit strong codependencies between Mexico, Brazil and Colombia on one hand and Colombia, Chile and Mexico on the other hand, as is also apparent in tables 7 and 8.

In table 8, we show the type of best fit copula for the present analysis. It can be seen that different copulas are used, conditioned across the same node implying divergent dependencies among the countries' EPU indexes. We notice that Frank copula appears the maximum time followed by Clayton, Gumbel and Gaussian copula with one entry each. **Generally speaking, the results of the full sample period are similar to the results of the post-GFC period in that most bivariate dependency structures are represented by copula families that don't exhibit tail dependencies. This highlights the appropriateness of considering sub-periods since it is apparent that the dependency structure between the countries underwent significant changes where in the pre-GFC period upper tail dependencies were more relevant than in the post-GFC period.** In addition, departing from previous studies (Albulescu *et al.* (2018); Allen *et al.* (2017)), we did not find any evidence of Student t copula, highlighting diminished importance of fat tails in any of the estimates for the pre-GFC, post-GFC and full sample periods which is also similar for the C-Vines results.

Table 7: R-Vine Copula Structure Matrix

$$\begin{bmatrix} BR & 0 & 0 & 0 \\ CL & CL & 0 & 0 \\ MX & CO & CO & 0 \\ CO & MX & MX & MX \end{bmatrix}$$

BR = Brazil, CL = Chile, CO = Colombia and MX = Mexico

Table 8: R-Vine Copula Specification Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	1	0	0	0
Colombia	5	5	0	0
Mexico	3	5	4	0

1 = Gaussian/Normal copula, 2 = Student t copula (t-copula), 3 = Clayton copula, 4 = Gumbel copula and survival Gumbel Copula, 5 = Frank copula, 6 = Joe copula

Table 9: R-Vine Copula Tau matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	0.085	0	0	0
Colombia	0.059	0.093	0	0
Mexico	0.114	0.173	0.142	0

From table 9, it is clear that the dependencies between the countries EPU indexes are strong and positive when the full sample period is considered. Further, we also note that the strongest and positive dependency is between Chile and Mexico while the weakest but positive dependency is documented for Brazil and Colombia. **Generally speaking, the Kendall's tau coefficient that we utilized to measure non-linear correlation is mostly positive in all the periods that we consider, implying that the indexes co-moved positively. Interestingly, the strongest value for the coefficient in both the pre-GFC period and the post-GFC period were exhibited by index pair Colombia&Mexico, a result that is also apparent in figure 1.**

4.2 Tail Dependence

As an additional robustness check for our results, we modeled tail dependence explicitly. Following the definitions as outlined in Joe (1997), we calculated the tail dependence parameter for the combinations that exhibited upper or lower tail dependency as follows[2]:

Table 10: Tail Dependence Coefficients

	Period	Copula parameter	λ_L	λ_U
Brazil & Colombia	Pre-GFC	1.02	-	0.03
Brazil & Mexico	Pre-GFC	1.28	-	0.28
Chile & Colombia	Pre-GFC	0.19	0.03	-
Chile & Mexico	Pre-GFC	1.50	-	0.41
Chile & Colombia	Post-GFC	1.11	-	0.14
Brazil & Mexico	Full Period	0.26	0.06	-
Colombia & Mexico	Full Period	1.16	-	0.19

As is clear from the table, both upper and lower tail coefficients imply a co-movement of EPU in the tails. In addition, upper tail coefficients are much higher than the lower tail coefficients in almost all cases, implying that co-movement in upper tails is much stronger than in the lower tail. Considering that no upper tail dependence is present in the post-2008 period, this supports our finding that contagion of uncertainty was significant in the pre-GFC period in the countries that we analyze.

To summarize our results, the application of R-Vine copulas in the present study allows us to capture the dependence structure between the EPU indexes of Brazil, Chile, Colombia and Mexico. The increase in the economic integration in terms of cross border trade and capital flows stirs the dependencies among these Latin American countries. We trace the dependencies among the nations determined by their EPU indexes during different time periods. About two-fifths of emerging markets' total trade is accounted for having trade with other emerging markets, which is almost double presently as compared to two decades ago (Kose *et al.* (2008)). Past studies such as the dividend discount model, project that the effect of any uncertainty (say GFC in this case) on the real economy would immediately affect the stock returns and several other factors related to the financial market (Gordon *&* Shapiro (1956)).

Similarly, there is also a possibility of effects of enduring uncertainty percolating from one economy to the other. Therefore, the economic uncertainty in one economy may penetrate the other economies through contagion. **Latin American countries have been subject to a myriad of analyses on contagion effects. While some authors established contagion effects in the exchange rates (e.g. Loaiza Maya *et al.* (2015)), others find that contagion in Latin American countries has been driven by strong asymmetric negative innovations in creditworthiness (Valdés (2000)).** The interdependencies between the EPU indexes between the nations in our study explain the persistence of contagion that differs from the pre-GFC and post-GFC periods as is evident

[2]We only report copula parameter estimates for combinations that exhibit tail dependence. Estimates for other combinations are available upon request

through differences in the copula structure and tail behavior. The present research shows that the economies investigated are closely interlinked, dissecting the decoupling debate about the economies' uncertainty conditions and contributing to the contagion literature.

5 Conclusion

As argued in Ozturk & Sheng (2018), the post-GFC period is marked by heightened uncertainty in trade, monetary policy and financial markets. Researchers in economics and finance pay more attention to the reasons behind financial crises and quantify interrelated economic phenomena, using various dependence measures. In this context, we investigated the co-dependencies between the EPU indexes of four Latin American countries. To achieve that, we employed a simple vine copula framework. There are several important results: the rank correlation coefficient (tau) matrices show that the dependency among the EPU indexes is mostly positive for the four countries considered, implying similar changes in economic policy uncertainty among the nations under consideration for the full sample period. For the pre-GFC and post-GFC period however, we find mixed signs for the countries' EPU indexes. Especially for country combinations involving Chile, there are multiple cases where the coefficient is negative, implying opposite movement of the EPU index.

Another important finding relates to the absence of Student t copula in the present study in all time periods considered, including financial turmoil, which highlights that symmetric tail dependencies are absent. Further, asymmetric tail dependencies, mostly in the form of upper tail dependency, are present when the pre-GFC period is considered. In contrast, there are no tail dependencies when the post-GFC period is considered. This may imply that after the global financial crisis of 2008, there was a decoupling in economic policy uncertainty among the countries considered and that as a result tail dependencies became less relevant. **Another implication of our results is that the contagion effect that was present in the 1990's mostly vanished after 2008, likely owing to the fact that policy-makers in Latin America implemented structural policies and were better equipped to tackle the effects of the 2008 global financial crisis. Previous analyses involving policy coordination (e.g. Allegret & Sand-Zantman (2009)) or policy convergence (Camarero *et al.* (2006)) in Latin American countries don't explicitly discuss the role of uncertainty in the feasibility of regional policy coordination. Our research may also provide useful information for this literature.**

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A C-Vine Copulas

C-Vine: Pre-GFC Period

Figure 5: Results C-Vine Tree-1 and 2, Pre-GFC

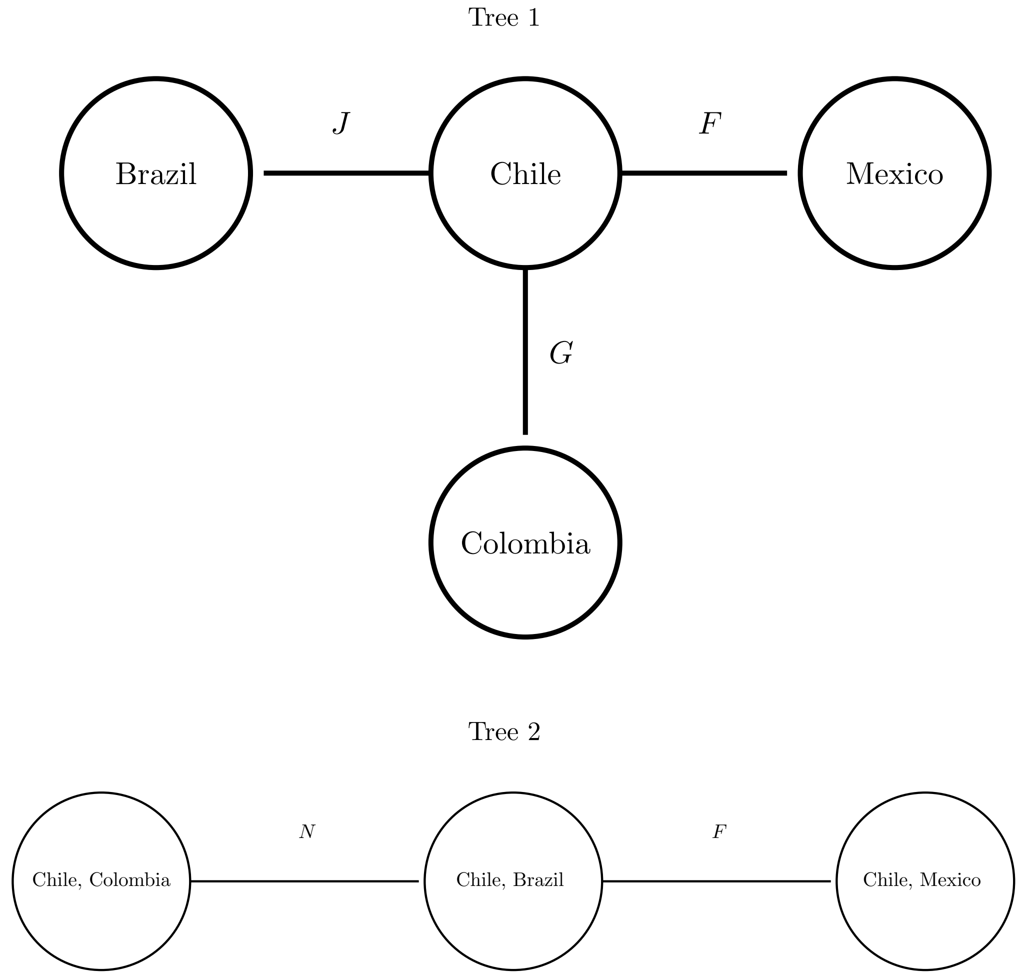

Table 11: C-Vine Copula Structure

	Brazil	Chile	Colombia	Mexico
Brazil	3	0	0	0
Chile	4	1	0	0
Colombia	1	4	2	0
Mexico	2	2	4	4

Table 12: C-Vine Copula Specification Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	3	0	0	0
Colombia	1	5	0	0
Mexico	4	6	5	0

Table 13: C-Vine Copula Tau Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	0.114	0	0	0
Colombia	0.112	-0.147	0	0
Mexico	0.331	0.110	0.347	0

C-Vine: Post-GFC Period

Figure 6: Results C-Vine Tree-1 and 2, Post-GFC

Tree 1

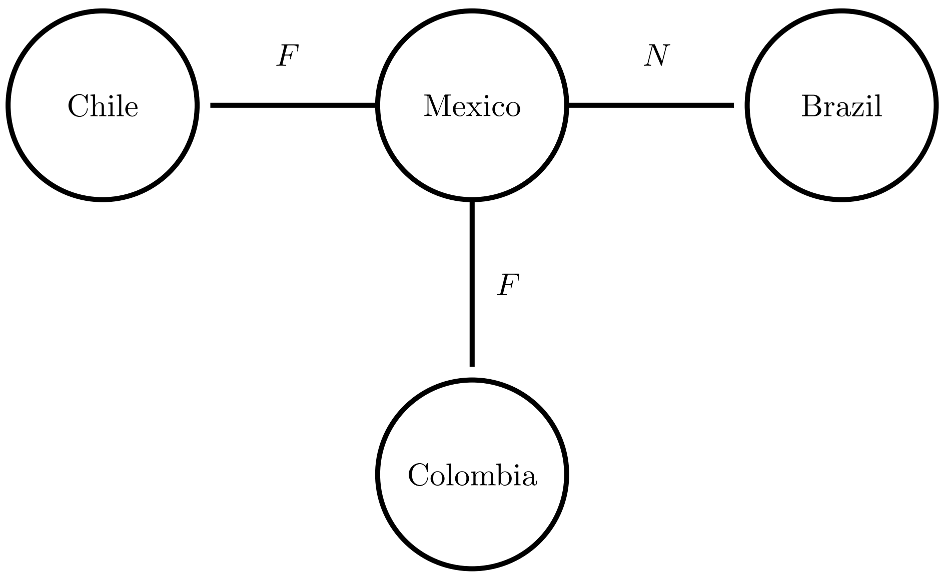

Table 14: C-Vine Copula Structure

	Brazil	Chile	Colombia	Mexico
Brazil	2	0	0	0
Chile	3	1	0	0
Colombia	1	3	3	0
Mexico	4	4	4	4

Tree 2

Table 15: C-Vine Copula Specification Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	5	0	0	0
Colombia	5	5	0	0
Mexico	5	1	5	0

Table 16: C-Vine Copula Tau Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	0.012	0	0	0
Colombia	0.276	0.139	0	0
Mexico	-0.147	-0.131	0.398	0

C-Vine: Full Sample Period

Figure 7: Results C-Vine Tree-1 and 2, Full Sample Period

Tree 1

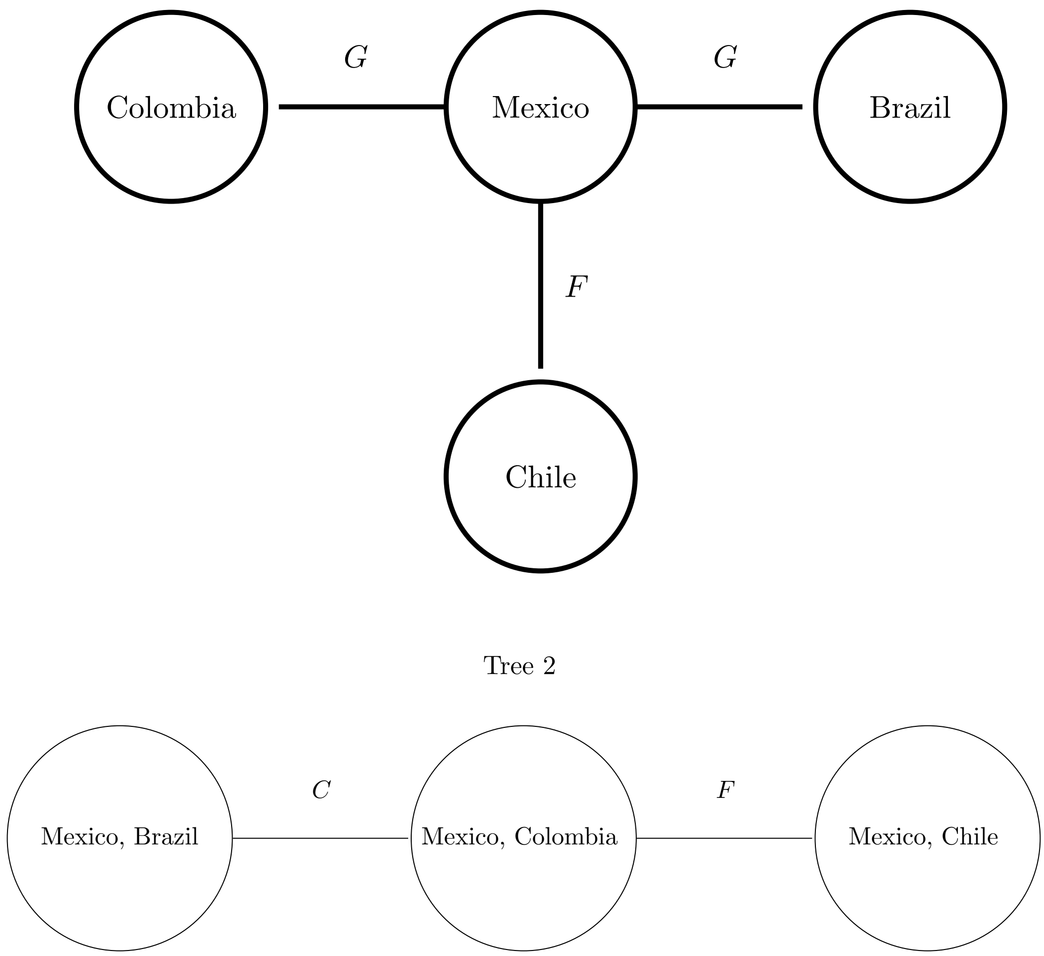

Table 17: C-Vine Copula Structure

	Brazil	Chile	Colombia	Mexico
Brazil	1	0	0	0
Chile	2	2	0	0
Colombia	3	3	3	0
Mexico	4	4	4	4

Table 18: C-Vine Copula Specification Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	1	0	0	0
Colombia	3	5	0	0
Mexico	4	5	4	0

Table 19: C-Vine Copula Tau Matrix

	Brazil	Chile	Colombia	Mexico
Brazil	0	0	0	0
Chile	0.082	0	0	0
Colombia	0.108	0.093	0	0
Mexico	0.076	0.173	0.142	0