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Sectoral Dependence and Contagion in the BRICS Grouping: an Application of the R-Vine copulas

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Abstract

Advances in portfolio optimisation techniques have given rise to studies that aim to identify changes in correlation structures between markets in times of economic turmoil. This phenomenon is known as contagion. This article aims at providing a new approach to distinguish between contagion and interdependence, where interdependence occurs when the correlation between two assets is not significantly different in tranquil and turmoil markets. An R-Vine Copula approach is considered to estimate the dependence structures and bivariate copulas between the estimated volatility of different markets. Thereafter, the tail dependence coefficients are estimated and a simulation procedure is used to determine their levels of significance.

This article also focusses on contagion and interdependence structures at a sectoral – rather than an aggregated – level of stock exchanges. Thus, this article analyses the contagion and interdependence structures of the Brazilian, Russian, Indian, Chinese, and South African financial, industrial, and resource sectors.

The estimated models indicate only a limited amount of contagion and interdependence events. This is in line with other authors who found that the Brazilian, Russian, Indian, Chinese, and South African economies can be seen as a heterogeneous asset class. In cases where there is strong co-movement, interdependence rather than contagion is observed. This suggests that strong market co-movements during periods of financial shock may be a continuation of strong cross-market linkages, i.e. interdependence instead of contagion.

Section 1 Introduction

Markowitz's (1952) Minimum Variance Portfolio Theory had a major effect on how portfolio allocation is considered. The main thrust of the ideology was that a portfolio should not only maximise future individual asset returns, but also minimise the correlations between said assets. Since then, methods based on asset correlation for portfolio selection have gained prominence in the financial economic literature (Elton, Gruber & Padberg, 1976; Ledoit & Wolf, 2004).

Other studies have also acknowledged the importance of asset correlation for portfolio selection, but have added that portfolio allocation should also consider changes in the correlation structure, depending on whether the economy is in a tranquil or turmoil market regime. For example, Campbell, Koedijk, and Kofman (2002) have considered time-varying correlation portfolio allocation strategies. These authors focussed on developing an estimator for correlation that considers the different market states. This allows a practitioner to use an amended variance-covariance matrix for mean-variance portfolio optimisation that incorporates the additional downside risk during turmoil market regimes.

Additionally, still in the context of rebalancing portfolios, studies have attempted to establish the extent to which correlations of asset returns increase during turmoil market regimes (Graflund & Nilsson, 2002; Pelletier, 2006; Ang & Bekaert, 2002; Ang, 2004). Besides assessing the magnitude of asset correlation during turmoil or tranquil periods, these studies also determine how an asset allocation strategy can be carried out by distinguishing between contagion (defined as a surge in correlation during turmoil market regimes) and interdependence (whereby the correlation during tranquil and turmoil market regimes are not significantly different).

While significant literature exists in distinguishing between contagion and interdependence, especially in the context of portfolio allocation, there is no consensus in terms of the methodology used to identify and distinguish between the two concepts. A number of studies focus on comparing the correlation structures between assets before and after a shock (King & Wadhwani, 1990). This type of comparison in correlation is in turn criticised by Forbes & Rigonon (2002), who proved that relying on the correlation estimate to distinguish between contagion and interdependence, without addressing the issue of heteroskedasticity, can lead to biased results. This is because the correlation estimate depends on the variance of both markets, which is naturally higher in turmoil times. Forbes and Rigonon (2002) and others (Boyer, Gibson & Loretan, 1999; Loretan & English, 2000) continued to study unbiased estimators of the correlation structures, but Corsetti, Pericoli, and Sbracia (2005) proved that these estimators' assumptions are too stringent.

Nevertheless, in distinguishing between contagion and interdependence, in the context of shock transmission and co-movement of important variables, different techniques are used, such as multiple regression techniques (Horen, Jager & Klaassen, 2006), regime switching models (Billio, Duca & Pelizzon, 2005), quantile regression (Ye, Luo & Liu, 2017), and Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) type models (Bonga-Bonga, 2018; Akhtaruzzaman & Shamsuddin, 2018). By using these techniques, these studies are able to distinguish between contagion and interdependence.

Extreme Value Theory is becoming a prominent testing technique in recent literature for establishing the presence of financial contagion (Longin & Solnik, 2001). The theory is used to identify the extent of contagion by determining whether significant correlations exist when extreme returns are observed. Furthermore, other authors have considered incorporating the Copula methodology with Extreme Value Theory to measure contagion (Costinot, Roncalli & Teiletche (2000) and Chan-Lau, Mathieson & Yao (2004)). When this methodology is used, it allows practitioners to estimate linear and non-linear correlation structures whilst utilising a host of symmetric and non-symmetric multivariate distributions. The methodology is important in the context of contagion, since it allows practitioners to identify the structure of linear or nonlinear relationships between assets' extreme values (Cubillos-Rocha, Gomez-Gonzalez & Melo-Velandia, 2019).

This article contributes to the literature in terms of how to identify and distinguish between contagion and interdependence by applying an R-Vine Copula methodology. Given that contagion is generally defined as the extent of transmission of shocks during a financial crisis, mainly represented by the negative tails of joint distributions of different markets or economies, this article will test the significance of the correlation on the extreme joint distribution of two different markets or economies based on the

R-Vine Copula methodology, to infer whether contagion or interdependence is present in the transmission of shocks between markets or economies. It is worth noting that past studies have used Extreme Value Theory to identify the existence of contagion (Cubillos-Rocha et al., 2019). However, these studies did not reach further and use the theory to distinguish between contagion and interdependence. Identifying whether changes in correlation structures are caused by contagion or interdependence significantly benefit asset managers and investors, with particular regards to investment and portfolio rebalancing strategies, since the correlation structure between different assets or markets is better understood. The study of contagion and interdependence is also a clear indicator of changes in relationships of financial assets post-crisis. Hence, it is important for policy-makers, since it may allow them to develop policies pre-emptively. Thus, this article proposes to distinguish between contagion and interdependence with the aid of Extreme Value Theory and the R-Vine Copula, by assessing the extent of shock transmission between different sectors of BRICS stock exchanges, namely the financial, industrial, and resource sectors. The study of the BRICS countries is of great importance for investors and asset managers because the BRICS grouping consists of five major emerging economies that provide 23.2% of the world GDP as of April 2018 (International Monetary Fund, 2018). The importance of conducting a study among the BRICS economies also arose out of the fact that in comparison to developed economies, emerging markets provide a higher return on capital (Henry, 2007) and are important hubs for international portfolio diversification.

The financial, industrial, and resource sectors were chosen to represent the main sources of growth for these countries, and to focus on the effect of the continuous effort to align their stances on regional, financial, and economic challenges (Info BRICS, 2019). Brazil provides exports in natural resources and holds the highest levels of gold and uranium deposits on earth. Their most valuable commodity is timber, and they supply 12.3% of the world's demand (Migiro, 2019). Russia is known for its mining activity and holds the sixth largest reserves of rare earth metals (Gambogi, 2005). India has realised growth in exporting IT services, and has the fourth largest vehicle industry in the world (India Brand Equity Foundation, 2019). China has the largest natural mineral deposits and leads the world as the largest manufacturing economy. South Africa's economy has mainly been driven by an abundance of gems and precious metals and the country is also the largest exporter of platinum globally (Workman, 2019).

The remainder of the study is structured as follows. Section 2 presents a literature review on the evolution of contagion models. Section 3 considers the econometric technique used in the study, namely, the Regular Vine Copula Methodology with the estimation and simulation of tail dependence coefficients. Section 4 presents the data and conducts the econometric estimation. In conclusion, section 5 provides a summary of the study and policy implications derived from the results.

Section 2 Literature Review

A broad range of authors have developed models to distinguish between interdependence and contagion. Initial studies on the subject focussed on testing whether or not correlations increased after economic shocks, with King and Wadhwani's (1990) seminal paper introducing this assumption into the literature. Using hourly stock market data from the New York, Hong Kong, and London stock exchanges before and after the October 1987 American stock market crash, the authors studied what the effect of an idiosyncratic shock in one market would be on another market, and how this shock might affect the correlation structure of the two markets. The authors found correlation increases after the stock market crash and concluded that contagion, rather than interdependence, exists between the markets. This research was extended by Lee and Kim (1993), who considered the weekly returns of 12 stock markets during the October 1987 crash period. The authors also considered whether or not significant changes in correlation were observed after the crash. The literature was extended by incorporating a factor analysis component, which was used to measure the relative importance before and after the crash of domestic and international factors in the investment decision-making process.

However, later studies have revealed that focussing solely on changes in correlations might lead to ambiguous results. Forbes and Rigobon's (2002) paper proves that a correlation estimate is biased and is in fact conditional on the market variance that provides the initial shock. This leads to the finding that heteroskedasticity in market indices will naturally lead to higher correlations during a financial crisis. Hence, a sole focus on the raw correlation estimate after a financial shock will, more often than not, lead to the spurious conclusion of contagion when, in fact, there is only interdependence at play between two indices. The authors proceed with this line of thought and provide a closed form expression for an unconditional correlation estimate under the assumptions of no exogenous global shocks and no feedback from the market that did not initially experience the shock. This methodology was tested by considering the contagion between the financial markets of 28 countries during the American stock market crash of 1987, the Mexican Peso crisis of 1994, and the East Asian crisis of 1997. A Vectorised Auto Regression (VAR) Model was applied to tranquil and turbulent periods to consider the changes in the variance-covariance structure. The American short-term interest rates, a country in crisis, and the corresponding country were also included for control variables. After applying the correction factor to the calculated correlations, it was determined that no contagion effect was truly present, but rather that interdependence of the market indices was present. Other researchers like Boyer et al. (1999) and Loretan and English (2000) also considered correcting for the bias in the correlation measure, but Corsetti et al. (2005) determined that the supposed results of these improvements were not realistic, as too stringent and unrealistic assumptions were made regarding the variance of the country-specific shocks.

To circumvent these issues, multiple regression techniques were also considered. Horen, Jager and Klaassen (2006) introduced the literature that discerns between interdependence and contagion using regression. The authors considered studying the existence of contagion effects during the Asian crisis of 1997 from the origin of the crisis, Thailand's exchange market, as well as the Philippine, Indonesian, Malaysian, and Korean exchange markets. The authors extended Girton and Roper's (1977) work by constructing an Exchange Market Pressure (EMP) variable as the response variable, which is a function of the change in each country's exchange rate, change in interest rate, and money supply. This was necessary as the bulk of the exchange rates considered were pegged against the US dollar. Finally, the authors modelled a country's EMP by considering a set of macro-economic factors and Thailand's EMP. To determine the degree to which contagion occurred, the authors also added a variable that was equal to zero in tranquil periods and equal to the EMP of Thailand during crisis periods. The coefficient of this variable indicated the degree of contagion from Thailand to other countries. If this state variable was significant, contagion was present. If not, only interdependence was observed. Evidence of contagion was found from Thailand to Indonesia and Malaysia, whereas interdependence was observed between Thailand and Korea and the Philippines. In line with this methodology, Billio et al. (2005) incorporated endogenous regime-switching by using Markov's Switching Error Correction Models. By doing so, the authors provided a way of ensuring that the crisis periods were endogenously defined instead of the researcher doing so arbitrarily. Moreover, by considering the estimated coefficient of the error correction term, the authors were able to directly test whether or not investors ignore economic fundamentals during times of economic crises. Furthermore, the authors distinguished between contagion and interdependence for the European stock market, the Hong Kong stock market, and the American Stock market during the Asian crisis of 1997. The authors found evidence for contagion between these markets, and by considering the error correction term, they could deduce that economic fundamentals tend to be ignored during crises. By utilising Time-varying Quantile Regression, Ye et al. (2017) studied contagion and interdependence between Asian, American, and European equity markets during the 2007-2009 US banking crisis and during the 2010 Greek sovereign bonds downgrade. The authors used the Quantile-specific Odds Ratio (QOR), which indicates the odds of two return indices simultaneously being below specified quantiles. This method has the added advantage of offering a clear interpretation as it is location- and scale-independent, thus providing a more transparent assessment of the local association structures. The authors found strong evidence of contagion from the US to all tested markets during the banking crisis. By comparison, the Greek sovereign bonds downgrade did not have as strong a contagion effect on the other markets, indicating that Greece may play a much more subdued role in the global economy. By utilising quantile regression, Lyocsa and Horvath (2018) also considered contagion from the US equity market to the equity markets of six developed countries. The authors also incorporated a wide array of control variables that considered the level and volatility in developed equity markets, gold and oil markets, foreign exchange markets, market liquidity, the credit market, and business cycle-related expectations. By controlling for these variables, the authors could test for contagion following Bekhaert, Harvey and Ng's (2005) definition. Billio et al. (2005) and Ye et al.'s (2017) definitions were combined by Ye, Zhu, Wu, and Miao's (2016), who used a Markov Regime-switching Quantile Regression Model to detect financial contagion. The authors continued to use this technique to determine changes in financial contagion, estimated through the quantile regression component, throughout different Markov states, i.e. different financial shock periods.

Authors like Bekhaert et al. (2005) circumvent correlation analysis. They used a two-factor asset-pricing model of a country's excess return to detect interdependence and contagion between European, Latin American, and Southeast Asian regions. The two factors were the regional equity portfolio return and the U.S. equity market return. The model's estimated coefficients were also allowed to be time-varying, allowing researchers to study varying degrees of market interdependence. The idiosyncratic shocks of the regional equity portfolio and the U.S. equity market return were also included in the two-factor model. This was expanded by modelling the idiosyncratic shocks with a GARCH model with asymmetry. Overall and period-specific contagion was then identified by studying the relationship between the different markets' residuals. The authors found that the Mexican Peso Crisis (1994) did not provide a significant surge in contagion between markets. However, the Asian Crisis (1997) shows clear evidence of being a contagious event, especially within the Oceanic countries. GARCH-type models have been used by a variety of authors. A VAR-DCC-GARCH model was employed by Bonga-Bonga (2018) to specifically assess contagion between South Africa and the other BRICS nations during global and BRICS-specific financial crises. The author's main findings were that capital market interdependence exists between Brazil and South Africa, and that the contagion effect of crises originating in Russia, India, and China on South Africa is greater than the contagion effect of crises originating in South Africa on the said countries. Akhtaruzzaman and Shamsuddin (2018) used a DCC-GARCH model to measure interdependence and contagion between the US and other developed, emerging and frontier economies. The main contribution was that the authors provided a disaggregated view by focussing on contagion between financial and non-financial firms. By using a Fractionally Integrated Asymmetric Power Auto Regressive Conditional Heteroscedasticity (FIAPARCH) model, Kenourgios and Dimitriou (2015) considered contagion on a sectoral level between six developed and emerging economies. The authors found that consumer goods, healthcare, and technology were less affected by the Global Financial Crisis (GFC).

The use of the Copula Methodology in the context of financial contagion has received much attention in recent literature. Costinot et al.'s (2000) inaugural study used Normal and Extreme Value Copulae to study interdependence and contagion during the Asian Crisis between the stock and exchange markets of Thailand, Korea, Malaysia, Philippines, and Indonesia. It was established that the main advantage of using the Copula methodology is the fact that it allows for the analysis of scenarios that go beyond normal dependence structures. Building on this, Chan-Lau et al. (2004) used Extreme Value Theory measures whilst utilising the Copula methodology. Specifically, they developed contagion measures for the bottom and top five per cent returns, hence defining bear and bull market contagions respectfully. By studying the weekly stock market returns of a wide range of mature and emerging economies, the authors' main findings were that there is a significant difference in the contagion patterns across regions. In addition, contagion is higher for negative returns, i.e. during bear markets. Hu (2006) used a Mixed Copula Approach to take account of various patterns in dependence structures. The authors considered a Gaussian Copula with no tail dependence, a Gumbel Copula with positive right tail dependence, and its survival counterpart with positive left tail dependence. By considering the weights of the mixed model, a researcher is able ascertain whether or not contagion exists, and can establish whether it is more prominent during positive or negative shocks. The author studied contagion between the S&P 500, FTSE, the Nikkei, and Hang Seng markets. The main finding was that only left tail dependence was observed, indicating that markets are expected to depreciate rather than appreciate together. Rodriguez (2007) used a Mixed Copula Approach with Markov switching parameters to discern between interdependence and contagion between four Latin American markets during the Mexican crisis of 1994, and five East Asian markets during the Asian crisis of 1997. The advantage of using this methodology is that determining periods of economic turmoil becomes endogenous to the model. In studying multivariate dependence structures, Chollete, Heinen and Valdesogo (2009) expanded on this by making a comparison between Mixed Copula Models and Canonical Vine Copulae. The authors established that Canonical Vine Copulae generally outperform Mixed Copulae, since the latter implicitly limits the feasible region of dependence between variables. The authors continued by utilising a Regime Switching Canonical Vine Copula Method to study the dependence structures between the G5 countries and Latin American regions. The two main findings were that Canonical Vine Copulae generally dominate alternative dependence structures and the choice of Copula can have a significant effect in modelling international portfolio returns. The Copula Method was also used by Horta, Mendes and Vieira (2010) during the US subprime crisis of 2007-2009 to test for interdependence and contagion from the US stock market to the stock markets of the Netherlands, Belgium, France, and Portugal. Hypothesis tests based on the Kendall's tau statistic were designed to test for the existence and the homogeneity of contagion from the US stock market to the other stock markets. The authors also develop a hypothesis test to test whether contagion to financial firms are the same as contagion to industrial firms. The authors found that there were no statistically significant differences in contagion when global or sectoral indices were considered.

Paul and Gideon (2017) studied the existence of interdependence and contagion between developed foreign exchanges and stock markets to African stock markets. The authors focussed on calculating the downside cumulative mean distribution Conditional Value-At-Risk (CoVaR) using Copula functions. They found that the effect of global shocks on African stock markets might only manifest post-crisis. Utilising the flexibility of Regular Vine Copulae, Cubillos-Rocha et al. (2019) studied contagion between developed and large developing economies and also considered whether or not contagion follows a geographical pattern. They found that contagion only occurs in times of currency appreciation with respect to the US dollar. The authors also established that whilst contagion is more observable within countries in similar regions, emerging market currencies are affected more by developed market currencies. This article extends the techniques introduced by Cubillos-Rocha et al. (2019) since the Regular Vine Copula Method allows for a multitude of different correlation structures that do not have to be predefined. Where the latter paper only focussed on identifying contagion, this study extends this line of literature in a methodological manner by attempting to distinguish between interdependence and contagion. This is extremely relevant to an investor as they can follow different investment strategies in the case of interdependence or contagion. This article also focusses on interdependence and contagion on a disaggregated level, i.e. by considering the BRICS countries' sectors. This is relevant because modern investors' diversification strategies could underestimate the correlation between different sectoral indices, thus unknowingly introducing additional risk into their portfolios.

Section 3 Methodology

This study uses the R-Vine Copula Approach to identify contagion and interdependence between the BRICS countries' sectors. The Regular Vine Copula Approach was first introduced by Joe (1997) and is considered to determine the most optimal multivariate dependence structure, after which the tail dependence coefficients are studied for evidence of contagion or interdependence.

Before this can be done, the Copula Approach requires the selection of the marginal models to be used. To distinguish between contagion and interdependence, it is necessary to use a marginal model to capture volatility shocks in each series. This study considers fitting the first two moments of each series with an $\mathrm{ARMA(p,q)} - \mathrm{GARCH(r,s)}$ model with student t innovation distribution. This set of models are chosen as the time series in question can be serially dependent and have non-constant, extreme variances. Thereafter, the fitted variance of each series is used as the marginal of the model, predicted using the fitted $\mathrm{ARMA(p,q)} - \mathrm{GARCH(r,s)}$ models.

3.1 Model for Marginal Distributions

After transforming the series into log-returns, the first two moments of each series are modelled using an $\mathrm{ARMA(p,q)} - \mathrm{GARCH(r,s)}$ Model with student t innovation distribution with ν_c degrees of freedom. It follows that each series will have a parameter set $\boldsymbol{\theta} = (p, q, r, s, \nu_c)$. If the log-returns are defined as $y_{c,t}$, with $c = 1, \dots, n$ an indicator for the series and $t = 1, .., T$ an indicator for time, the $\mathrm{ARMA(p,q)} - \mathrm{GARCH(r,s)}$ model can be defined as:

$$y_{c,t} = \mu_c + \sum_{i=1}^{p} \varphi_{c,i} y_{c,t-i} + \sum_{i=1}^{q} \theta_{c,i} \varepsilon_{c,t-i} + \varepsilon_{c,t} \tag{1}$$

$$\varepsilon_{c,t} = \eta_{c,t} \sqrt{h_{c,t}} \tag{2}$$

$$h_{c,t} = \omega_c + \sum_{i=1}^{r} \alpha_{c,i} h_{c,t-i} + \sum_{i=1}^{s} \beta_{c,i} \varepsilon^2{}_{c,t-i} \tag{3}$$

where $\eta_{c,t}$ follow a student t innovation distribution with ν_c degrees of freedom. The model specification $\boldsymbol{\theta}$ is determined iteratively for each series by first fitting a range of models using the model specification $\boldsymbol{\theta}_i = (\mathrm{p_i}, q_i, r_i, s_i, \nu_c)$, with $\mathrm{p_i}, \mathrm{q_i}, r_i, s_i = 0, \dots, 4$. In alignment with Patton (2006), Jondeau and Rockinger (2006), De Lira Salvatierra &

Patton (2015), and BanSaida (2018), the Portmanteau Test for Time-based Dependence, or BDS test, is used to test the null hypothesis of independent identically distributed (IID) residuals. Finally, the most parsimonious model that fails to reject this null hypothesis is chosen. After the final model is estimated, the estimated variance of each series is determined, which is then transformed to $x_{c,t} \in [0,1]$ using the Probability Integral Transform (PIT). This is used to estimate the R-Vine Copula structure.

3.2 R-Vine Copula Estimation

The advent of the Copula Methodology is attributed to Sklar's Theorem (Sklar, 1959), which states that if $F(x_1, \dots, x_n)$ is an n-dimensional joint distribution function, with marginal distributions $F_1(x_1), F_2(x_2), \dots, F_n(x_n)$ of the random variables $X_1, X_2, \dots, X_n$, then there exists a unique Copula function C, such that for all $x_1, x_2, \dots, x_n$,

$$F(x_1, \dots, x_n) = C(F_1(x_1), F_2(x_2), \dots, F_n(x_n)). \tag{4}$$

By using the chain rule, one can express the n-dimensional joint densify function as

$$f(x_1, x_2, \dots, x_n) = c_{1\dots n}(F_1(x_1), F_2(x_2), \dots, F_n(x_n)) \prod_{c=1}^{n} f_c(x_c). \tag{5}$$

While the Copula Methodology is adequate for simpler correlation structures, a problem arises when the dependence structures of variables in a multivariate setting are very different. This lead to Joe's (1996) introduction of the Pair Copula Construction (PCC), allowing for the expression of the joint density function as a product of the marginal distributions and bivariate Copulae, i.e.

$$f(x_1, x_2, \dots, x_n) = f_n(x_{n-1}).f_{n-1|n}(x_{n-1}|x_n).f_{n-2|n-1,n}(x_{n-2}|x_{n-1}, x_n) \dots f_{1|2,\dots,n}(x_1|x_2, \dots, x_n) \tag{6}$$

with

$$f(x_c, \mathbf{X}) = c_{x_c \mathrm{X}_j|\mathbf{X}_{-j}}\left(F\left(x_c|\mathbf{X}_{-j}\right), F\left(\mathrm{X}_j|\mathbf{X}_{-j}\right)\right) f\left(x_c|\mathbf{X}_{-j}\right), \tag{7}$$

where the conditioning set of x_c is $\mathbf{X} = \{x_{c+1}, \dots, x_d\}$; X_j is a variable contained in the set, $\mathbf{X}$, $\mathbf{X}_{-j}$ are the remaining elements, and $c(x_1, x_2) = \frac{\partial C(x_1, x_2)}{\partial x_1 \partial x_2}$.

The usual representation of the PCC is that of nested trees $T_i = \{N_i, E_i\}$, which are acyclical graphs with nodes N_i and edges E_i (Bedford & Cooke, 2001). The R-Vine developed by Bedford and Cooke (2002) is represented by a nested set of $n-1$ trees

$\boldsymbol{\mathcal{V}} = (T_1, \dots, T_{n-1})$, with a set of edges E_i and nodes $N_i = \{1, \dots, n-i\} = E_{i-1}$, where two nodes in tree $i+1$ are connected by one edge only if they share a common node in tree i.

The R-Vine Copula used in this study is a general case of the PCC. It is represented as $(\boldsymbol{F}, \boldsymbol{\mathcal{V}}, \mathbf{B})$, with $\boldsymbol{F} = (F_1(x_1), \dots, F_n(x_n))$ a vector of distribution functions, $\boldsymbol{\mathcal{V}}$ an n-dimensional R-Vine, and $\boldsymbol{B} = \{B_e | i = 1, \dots, n-1; e \in E_i\}$ a set of bivariate Copulae (Dißmann, Brechmann & Czado, 2013).

To facilitate Dißmann et al.'s (2013) estimation procedure, the R-Vine structure can be denoted as a lower triangular matrix

$M = (m_{i,j})_{i,j=1,\dots,n}$.

The matrix $M = (m_{i,j})_{i,j=1,\dots,n}$ is called an R-Vine matrix if for $i = 1, \dots, n-1$ and for all $k = i+1, \dots, n-1$ there is a j in $i+1, \dots, n-1$ with

$\left(m_{k,i}, \{m_{k+1,i}, \dots, m_{n,i}\}\right) \in B_M(j)\ or\ \in \tilde{B}_M(j)$ where

$B_M(j) = \{(m_{j,j}, D) | k = j+1, \dots, n; D = \{m_{k,j}, \dots, m_{n,j}\}\}$, and

$\tilde{B}_M(j) = \{(m_{k,j}, D) | k = j+1, \dots, n; D = \{m_{j,j}\} \cup \{m_{k+1,j}, \dots, m_{n,j}\}\}$.

The density of an R-Vine copula is then expressed as

$$f_{1,\dots n} = \prod_{j=1}^{n} f_j \prod_{k=n-1}^{1} \prod_{i=n}^{k+1} c_{m_{k,k} m_{i,k} | m_{i+1,k} \dots m_{n,k}} \left(F_{m_{k,k} | m_{i+1,k}, \dots, m_{n,k}}, F_{m_{i,k} | m_{i+1,k}, \dots, m_{n,k}}\right). \quad (8)$$

From this, Dißmann et al. (2013) propose the following estimation procedure for each tree in $\boldsymbol{\mathcal{V}}$, which is followed in this study:

1. for each pair of variables, determine the estimate of the Kendall's tau;
2. calculate the sum of the absolute Kendall's taus and choose the tree structure where this is maximised;
3. estimate the appropriate Copula families given the tree structure in step 2 using the AIC criterion;
4. save the transformed observations for the next tree to be calculated; and
5. reiterate through steps (1)-(4) until the full tree structure is estimated.

After the R-Vine copula structure is estimated, the tail dependence coefficients are estimated (Joe, 1997). The statistical significance of these values is determined through the simulation procedure proposed by Cubillos-Rocha et al. (2019).

3.3 Tail Dependence Coefficients

The R-Vine structure can be used to provide an estimate of the upper and lower tail dependence between the variables. It is in that context that the tail dependence coefficients (TDC) in terms of Copulae developed by Joe (1997) is considered. If X_1 and X_2 are two series with corresponding cumulative distribution functions, F_1 and F_2 respectively, the upper and lower tail dependence coefficients are defined as:

$$\lambda_U = \lim_{u \to 1^-} P(X_1 > F_1^{-1}(u) | X_2 > F_2^{-1}(u)$$

$$= \lim_{u \to 1^-} \frac{1-2u+C(u,u)}{1-u} \tag{9}$$

$$\lambda_L = \lim_{u \to 0^+} P(X_1 < F_1^{-1}(u) | X_2 < F_2^{-1}(u)$$

$$= \lim_{u \to 0^+} \frac{C(u,u)}{1-u} \tag{10}$$

Note that Joe (1997) proved the tail dependence coefficients were symmetric, i.e.

$$\lim_{u \to 1^-} P(X_1 > F_1^{-1}(u) | X_2 > F_2^{-1}(u) = \lim_{u \to 1^-} P(X_2 > F_2^{-1}(u) | X_1 > F_1^{-1}(u))$$

and

$$\lim_{u \to 0^+} P(X_1 < F_1^{-1}(u) | X_2 < F_2^{-1}(u) = \lim_{u \to 0^+} P(X_2 < F_2^{-1}(u) | X_1 < F_1^{-1}(u)).$$

To estimate equations (9) and (10), the empirical Copula $\hat{C}(u,u)$, as defined by Deheuvels (1980), is used. This changes the expressions to

$$\hat{\lambda}_U = \lim_{i_U \to N^-} \frac{1-2\frac{i_U}{N}+\hat{C}(\frac{i_U}{N},\frac{i_U}{N})}{1-\frac{i_U}{N}} \tag{11}$$

$$\hat{\lambda}_L = \lim_{i_L \to 0^+} \frac{\hat{C}(\frac{i_L}{N},\frac{i_L}{N})}{1-\frac{i_L}{N}} \tag{12}$$

The following simulation exercise proposed by Cubillos-Rocha et al. (2019) is used to determine the statistical significance of the TDCs:

1. with the R-Vine structure defined, simulate 10 000 observations of the variables utilising the algorithms developed by Dißmann et al. (2013);
2. calculate $\hat{\lambda}_U$ and $\hat{\lambda}_L$ from the simulated observations;
3. reiterate through steps (1) and (2) S = 500 times;
4. use the mean value of the calculated TDCs as the final TDC values; and
5. use the empirical distribution function of the TDCs for $\left(1-\frac{\alpha}{2}\right)100\%$ confidence intervals to determine the level of significance.

With the upper and lower TDC's defined, one can formulate a more concrete hypothesis. Since the estimated variances of each series are used for the marginal models, this study argues that if there is significant dependence only in the upper tail of the joint distribution of two different variances, then contagion is observed. On the other hand, if there is significant dependence in both the upper and lower tail of the joint distribution, then interdependence is observed.

Section 4 Data and Results

Daily data over the period of January 2006 to May 2019 was used in this study. This period was chosen in order to include major events from a BRICS and an international perspective. The financial, industrial, and resource sectors are chosen to represent the main sources of growth for these countries, and to focus on the effect of the continuous effort to align their stances with regional, financial, and economic challenges (Info BRICS, 2019). The returns from the respective sectors were computed using indices registered on the BOVESPA for Brazil, the MOEX for Russia, the NSE for India, the SSE for China, and the JSE for South Africa. The estimated variances for these returns were then used to discern between contagion and interdependence between the relevant sector indices.

Table 1: Descriptive Statistics

Country	Sector	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera test statistic
Brazil	*Financial*	0.0006	0.0187	0.3332	7.5905	8528.9060
	Industrial	0.0003	0.0143	-0.2030	8.2953	10132.2409
	Resource	0.0003	0.0076	0.3441	11.3844	19105.4862
China	*Financial*	0.0001	0.0137	-0.2478	6.6035	6442.2466
	Industrial	-0.0001	0.0145	-0.5560	6.6880	6752.5984
	Resource	-0.0001	0.0142	-0.7484	6.5865	6702.1623
India	*Financial*	0.0006	0.0174	0.0898	7.2696	7768.0500
	Industrial	-0.0005	0.0258	-0.4812	8.3193	10302.6135
	Resource	-0.0001	0.0137	0.0283	2.5987	993.3937
Russia	*Financial*	0.0002	0.0198	-0.2186	21.8277	69997.6498
	Industrial	-0.0002	0.0189	-0.7171	32.3498	153981.0773
	Resource	0.0004	0.0196	-0.7152	15.2073	34264.8387
South Africa	*Financial*	0.0004	0.0098	-0.3296	4.9218	3623.1129
	Industrial	0.0007	0.0086	-0.1438	2.9024	1250.5025
	Resource	-0.0002	0.0130	-0.0592	2.8383	1186.3824

Summary statistics for the daily index log returns of the five BRICS countries' sectors are reported in Table 1. The mean levels were all close to 0, with India's Industrial sector providing the lowest return level. Brazil provided the best overall return with all their sectors having positive returns. The highest standard deviation was observed in India's industrial sector, whereas Brazil's resource sector had the lowest standard deviation. Most indices illustrated negative skewness, i.e. a long left tail, indicating that extreme negative returns were observed. The indices with positive skewness were Brazil's financial and resource sectors, and India's financial and resource sectors. Most of the indices also showed very high levels of kurtosis, most notably being

Russia's industrial sector with 32.3498. This indicates that most series had very heavy tails and suffered from extreme outliers. The lowest kurtosis levels were observed in India's resource sector. However, most notable were the indices of the South African sectors, which were markedly near normal, except for the financial sector, which showed excess kurtosis of approximately 2. Finally, none of the Jarque-Bera Test statistics were found to be significant, indicating substantial non-normality.

Table 2: Pearson correlation coefficients. The labels are shortened for brevity

	B F	B I	B R	C F	C I	C R	I F	I I	I R	R F	R I	R R	S F	S I	S R
B F	1.00	0.78	-0.05	0.07	0.03	0.01	0.26	0.19	0.10	0.31	0.15	0.29	0.13	0.11	0.11
B I	0.78	1.00	-0.04	0.08	0.05	0.02	0.27	0.22	0.11	0.34	0.14	0.33	0.11	0.11	0.10
B R	-0.05	-0.04	1.00	0.01	-0.01	0.03	0.01	0.01	0.00	-0.01	0.02	0.02	0.01	-0.02	0.00
C F	0.07	0.08	0.01	1.00	0.36	0.37	0.09	0.09	0.15	0.07	0.06	0.07	0.14	0.14	0.10
C I	0.03	0.05	-0.01	0.36	1.00	0.48	0.07	0.04	0.09	0.05	0.04	0.03	0.09	0.11	0.06
C R	0.01	0.02	0.03	0.37	0.48	1.00	0.04	0.05	0.12	0.05	0.03	0.03	0.08	0.09	0.10
I F	0.26	0.27	0.01	0.09	0.07	0.04	1.00	0.70	0.31	0.28	0.17	0.28	0.12	0.13	0.11
I I	0.19	0.22	0.01	0.09	0.04	0.05	0.70	1.00	0.34	0.24	0.13	0.23	0.10	0.10	0.08
I R	0.10	0.11	0.00	0.15	0.09	0.12	0.31	0.34	1.00	0.11	0.14	0.11	0.23	0.22	0.22
R F	0.31	0.34	-0.01	0.07	0.05	0.05	0.28	0.24	0.11	1.00	0.29	0.70	0.11	0.13	0.14
R I	0.15	0.14	0.02	0.06	0.04	0.03	0.17	0.13	0.14	0.29	1.00	0.20	0.14	0.10	0.19
R R	0.29	0.33	0.02	0.07	0.03	0.03	0.28	0.23	0.11	0.70	0.20	1.00	0.09	0.09	0.13
S F	0.13	0.11	0.01	0.14	0.09	0.08	0.12	0.10	0.23	0.11	0.14	0.09	1.00	0.51	0.28
S I	0.11	0.11	-0.02	0.14	0.11	0.09	0.13	0.10	0.22	0.13	0.10	0.09	0.51	1.00	0.36
S R	0.11	0.10	0.00	0.10	0.06	0.10	0.11	0.08	0.22	0.14	0.19	0.13	0.28	0.36	1.00

The Unconditional Pearson's Correlation is computed to assess the correlation in different sectors between and within countries. The results reported in Table 2 indicate that there are some instances in which the positive correlations are high, but this is mostly observed within a country. Examples of this include the correlation between Brazil's industrial and financial sectors, with a correlation coefficient of 0.78, and India's industrial and financial sectors with a correlation coefficient of 0.70. Conversely, negative correlations are rarely seen. The most negative correlation observed was again within a country, between Brazil's financial and resource sectors, with a correlation coefficient of -0.05. Although these results do not seem to suggest the possibility of efficient portfolio selection using the different BRICS assets, it is prudent to note the serious limitations of Unconditional Pearson Correlation Coefficients in this setting (Cubillos-Rocha et al., 2019). Moreover, while the dominating positive correlation between these assets may be indicative of sectorial co-movement in BRICS, possibly due to contagion, it is important to bear in mind that these correlations do not provide an indication as to whether correlations differ in normal or turbulent times, which would confirm the presence contagion or interdependence. The results reported in Table 2 should be seen as an indication of linear association, which can be limiting when higher order relationships are also required. Finally, because of the data's high frequency, significance tests become ever more questionable. Copula functions provide us with useful tools to overcome all the limitations of Unconditional Pearson's Correlations.

The first step in the Copula Methodology is to find the appropriate marginal models for the different indices. Hence, the first two moments of each series are modelled with an $\mathrm{ARMA(p,q)} - \mathrm{GARCH(r,}s)$ model with student t innovation distribution as expressed in equation (1) - (3). This set of models is chosen since each time series in question can be serially dependent and have non-constant, extreme variances. Using BanSaida's (2018) procedure, the parameter set $\boldsymbol{\theta} = (p, q, r, s, v)$ for each marginal model is chosen such that the residuals are independent and identically distributed. The results of the estimated parameter $\boldsymbol{\theta}$ of $ARMA(p, q) - GARCH(r, s)$ models for each series are reported in Table 3[1].

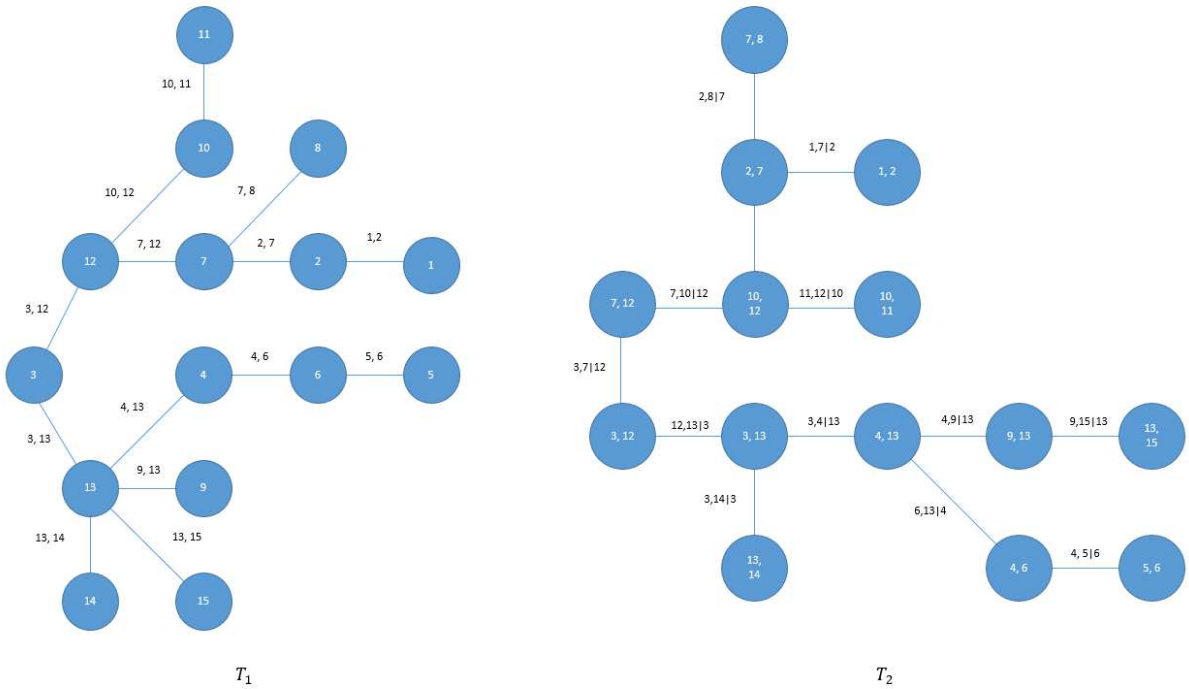
Table 3: Marginal model specification

Country	Sector	p	q	r	s	BDS p-value
Brazil	*Financial*	4	4	3	2	0.6600
	Industrial	2	2	4	3	0.8746
	Resource	4	4	1	4	0.2741
China	*Financial*	3	4	3	1	0.0642
	Industrial	0	2	3	3	0.0600
	Resource	4	4	3	4	0.2838
India	*Financial*	3	4	3	3	0.9964
	Industrial	1	2	2	1	0.0600
	Resource	4	4	4	4	0.0499
Russia	*Financial*	3	1	1	3	0.0600
	Industrial	4	3	3	2	0.0600
	Resource	4	4	1	3	0.2274
South Africa	*Financial*	4	4	4	1	0.1261
	Industrial	2	4	4	3	0.0600
	Resource	0	3	4	2	0.0600

Using the fitted variances derived from the specified $ARMA(p, q) - GARCH(r, s)$ models as the marginal, the regular vine structure is estimated using Dißmann et al.'s

[1] The coefficients of the mean and conditional variance equations can be provided on request.

(2013) procedure. The appropriate tree structure is determined by maximising the sum of the absolute Kendall taus. Since it is impractical to visualise the full set of 14 trees, only the first two are depicted in Figure 1.



[2]

Figure 1: R-Vine tree structure.

Figure 1 shows that the definition of the R-Vine tree structure has been followed, i.e. that a node in tree two (T_{i+1}) must be an edge in tree one (T_i). As an example, one can consider the edge denoted as (10, 12) that forms between Russia's financial sector (node 10) and Russia's resource sector (node 12). In turn, this edge is used as a node in tree two. Since the tree structures are determined by maximising the sum of the absolute Kendall's taus between all nodes, this result can be seen as indicative of a relationship between Russia's financial and resource sectors. All further trees naturally followed the same pattern as per the definition.

After this, the appropriate Copula families – given the tree structure – are determined using the AIC criterion. Maximum likelihood estimation is then used to determine each Copula's parameters. Thirty-nine different copulas were considered for each bivariate

[2] The numbers indicate the countries and sectors as follows: 1=Brazil financials, 2=Brazil Industrials, 3=Brazil Resources, 4=China Financials, 5=China Industrials, 6=China Resources, 7=India Financials, 8=India Industrials,
9=India Resources, 10=Russia Financials, 11=Russia Industrials, 12=Russia Resources, 13=South Africa Financials, 14=South Africa Industrials, 15=South Africa Resources

Copula specification. They are the Gaussian Copula, the Student t Copula (t-copula), the Frank Copula, the Clayton Copulae (standard, rotated $90°$, $180°$, and $270°$), the Gumbel Copulae (standard, rotated $90°$, $180°$, and $270°$), the Joe Copulae (standard, rotated $90°$, $180°$ and $270°$), the BB1 Copulae (standard, rotated $90°$, $180°$, and $270°$), the BB6 Copulae (standard, rotated $90°$, $180°$, and $270°$), the BB7 Copulae (standard, rotated $90°$, $180°$, and $270°$), the BB8 Copulae (standard, rotated $90°$, $180°$, and $270°$), the Tawn Type 1 Copulae (standard, rotated $90°$, $180°$, and $270°$) and the Tawn Type 2 Copulae (standard, rotated $90°$, $180°$, and $270°$). The estimated bivariate Copulae and their corresponding parameters are illustrated in Appendix A for completeness. The results in Appendix A indicate that there were interesting relationships between most of the sectors considered. The symmetric T Copula and Gaussian Copula were rarely used, and the Independence Copula was only used between Brazil's financial sector and China's financial sector.

After the R-Vine Copula structure, Copula families and relevant parameters were estimated, the tail dependence coefficients (TDCs) were estimated (Joe, 1997) and statistical significance was determined using the simulation procedure provided by Cubillos-Rocha et al. (2019). In each of the $S = 500$ simulations, $N = 10{,}000$ samples were drawn from the 15 indices and the TDCs were calculated. The lower and upper thresholds for the TDCs expressed in equations (11) and (12) were $i_L = 0.01$ and $i_U = 0.99$, respectfully.

The values illustrated in Table 4 represent the mean values of the TDCs and the significance levels were determined using the $\left(1 - \frac{\alpha}{2}\right) 100\%$ confidence intervals created by simulations. The top right panel of Table 4 shows the upper TDCs, whereas the lower TDCs are presented in the bottom left panel. To discern between contagion and interdependence, it is necessary to consider the upper and lower TDCs simultaneously. If both the upper and lower TDC are significantly different from zero, then interdependence is observed, as there are strong relationships between the indices, regardless of whether small or large variances are observed. On the other hand, if only the upper TDC is significant, it can be assumed that contagion is observed, since significant co-movement of variances is only observed during extreme variances.

Table 4[3]: Tail dependence coefficients for the 15 indices.

		Brazil			Russia			India			China			South Africa		
		Financial	Industrial	Resource	Financial	Industrial	Resource	Financial	Industrial	Resource	Financial	Industrial	Resource	Financial	Industrial	Resource
Brazil	Financial	.	0.5994*	0.0510	0.2885	0.0958	0.3079	0.3000	0.2731	0.0138	0.0011	0.0113	0.0079	0.0190	0.0273	0.0246
	Industrial	0.0016*	.	0.0854	0.4023*	0.1332	0.4462*	0.4336*	0.3970	0.0127	0.0044	0.0121	0.0075	0.0090	0.0153	0.0072
	Resource	0.0003	0.0006*	.	0.0594	0.0117	0.0587	0.1066	0.0925	0.0066	0.004	0.0129	0.0024	-0.0018	-0.0007	0.0017
Russia	Financial	0.0013*	0.0013*	0.0008*	.	0.2487	0.6898*	0.4273*	0.3784*	0.0045	-0.0013	0.0087	0.0019	-0.0016	0.0122	0.0012
	Industrial	0	0.0001	0	0.0002	.	0.217	0.1309	0.1290	0.0105	0.0299	0.0331	0.0315	0.0054	0.0206	0.0189
	Resource	0.0005	0.0018*	0.0003	0.0013*	0.0001	.	0.5053*	0.4438*	0.0058	0	0.0107	0.0045	0.0002	0.0130	0.0026
India	Financial	0.0002	0.0002	0.0009*	0.0006*	0.0001	0.0016*	.	0.7011*	0.0116	0.0019	0.0166	0.0064	0.0049	0.0083	0.0034
	Industrial	0.0003	0.001*	0.0005*	0.0006*	0.0001	0.001*	0.0015*	.	0.0137	0.0036	0.0170	0.0072	0.0040	0.0072	0.0028
	Resource	0.0002	0	0	0.0001	0.0005	0	0	0	.	0.0387	0.0176	0.0354	0.0569	0.0359	0.0693
China	Financial	0.0001	0.0001	0.0006*	0.0003	0.0002	0.0004	0.0008*	0.0003	0.0003	.	0.4148*	0.5723*	0.0537	0.0520	0.2144
	Industrial	0.0005	0.0001	0.0003	0.0004	0.0001	0.0004	0.0014*	0.0004	0.0001	0.001*	.	0.5476*	0.0798	0.0530	0.1497
	Resource	0.0001	0.0001	0.0003	0.0002	0.0001	0.0002	0.0008*	0.0002	0.0002	0.002*	0.0004*	.	0.1517	0.0843	0.2049
South Afric	Financial	0.0002	0.0002	0	0.0001	0.0003	0.0004	0.0001	0.0001	0.0005	0.0002	0.0002	0.0003	.	0.1598	0.1435
	Industrial	0.0001	0.0001	0	0.0001	0.0002	0.0001	0	0	0.0004	0.0002	0.0002	0.0002	0.0004	.	0.0691
	Resource	0.0002	0.0001	0	0.0001	0.0004	0	0	0	0.0011*	0.0002	0.0001	0.0003	0.0004	0.0003	.

[3] 1% level of significance indicated with an asterisk.

Table 4 indicates that only a few sectors illustrate contagion or interdependence. For example, from the results illustrated in Table 4, South Africa illustrates no relationships with any of the other countries in the BRICS grouping. This is in line with numerous studies that question the validity of including South Africa within the BRICS grouping (Smith, 2013; Davies, 2013; Anuoluwapo, Abdul-Wasi & Edwin, 2018; Bonga-Bonga, 2017). These authors argue that South Africa is an unlikely fit for the BRICS grouping since it does not share the same characteristics as the other countries do, namely, large populations or rapid economic growth. However, it should be noted that the tail dependence coefficients used in this study were symmetrical measures (Joe, 1997). Thus, if a relationship is only unidirectional, the TDCs may fail to identify it. This may explain why the TDCs indicated no relationship, whilst other authors have identified that South Africa might be affected by other countries within the BRICS grouping, even though South Africa appears not to influence the other countries (Bonga-Bonga, 2018).

Country-specific network diagrams are provided in figure (2) – (6) to visually illustrate the details of the results presented in Table 4. Solid lines indicate cases where interdependence is observed, while dashed lines correspond with cases where contagion is observed. The indices *F, I, and R* represent the countries' financial, industrial, and resource sectors respectively.

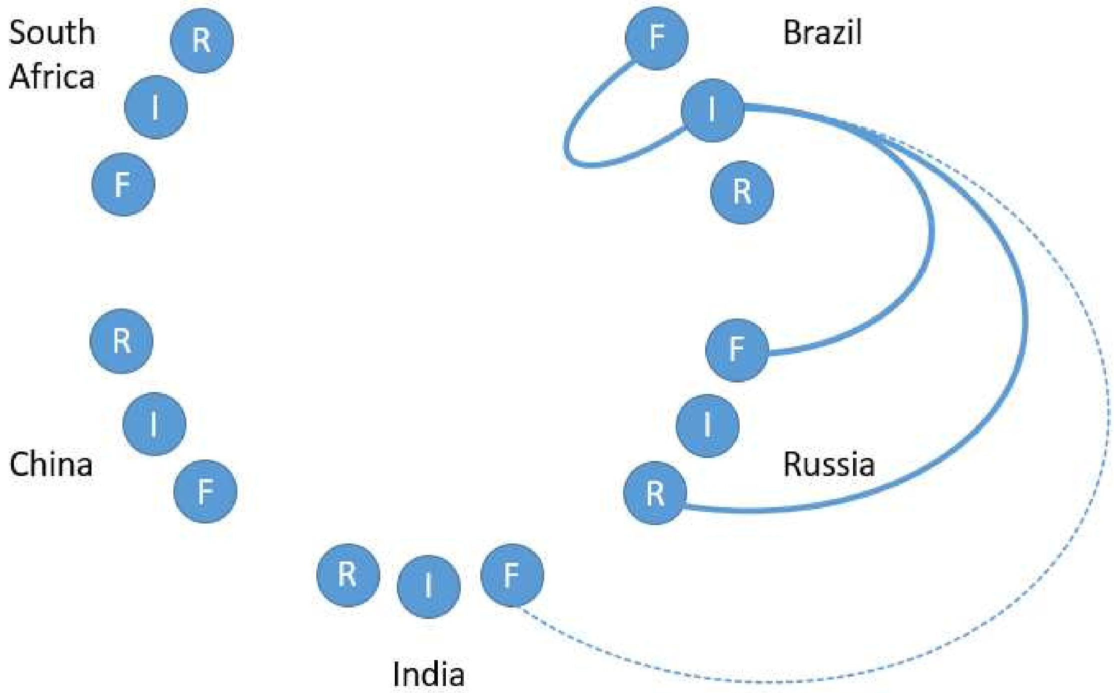


Figure 2: Brazilian network diagram

Based on the results presented in Table 4, figure 2 illustrates all the interdependence and contagion events associated with Brazil. Interdependence was observed between Brazil's financial and industrial sectors. Additionally, Brazil's industrial sector was the only sector that experienced contagion or interdependence with sectors outside of Brazil. The industrial sector experienced interdependence with the Russian financial and resource sectors. Also, it experienced contagion with the Indian financial sector. Furthermore, no contagion or interdependence was observed between Brazil and China. This implies that extreme shocks in China's economy do not impact Brazil significantly. This is interesting, since China is one of Brazil's biggest import and export trading partners. It should also be noted that the Brazilian resource sector does not share contagion or interdependence with other sectors. This might be explained by the fact that Brazil is known for its resource exports. As of 2017, Brazil's main exports consisted of raw mineral products (20%), raw vegetable products (17%), and foodstuffs (12%) (Simoes, 2019). With the exception of some items within the mineral products grouping, such as iron ore and crude oil, most of these items are mostly insensitive to extreme market movements.

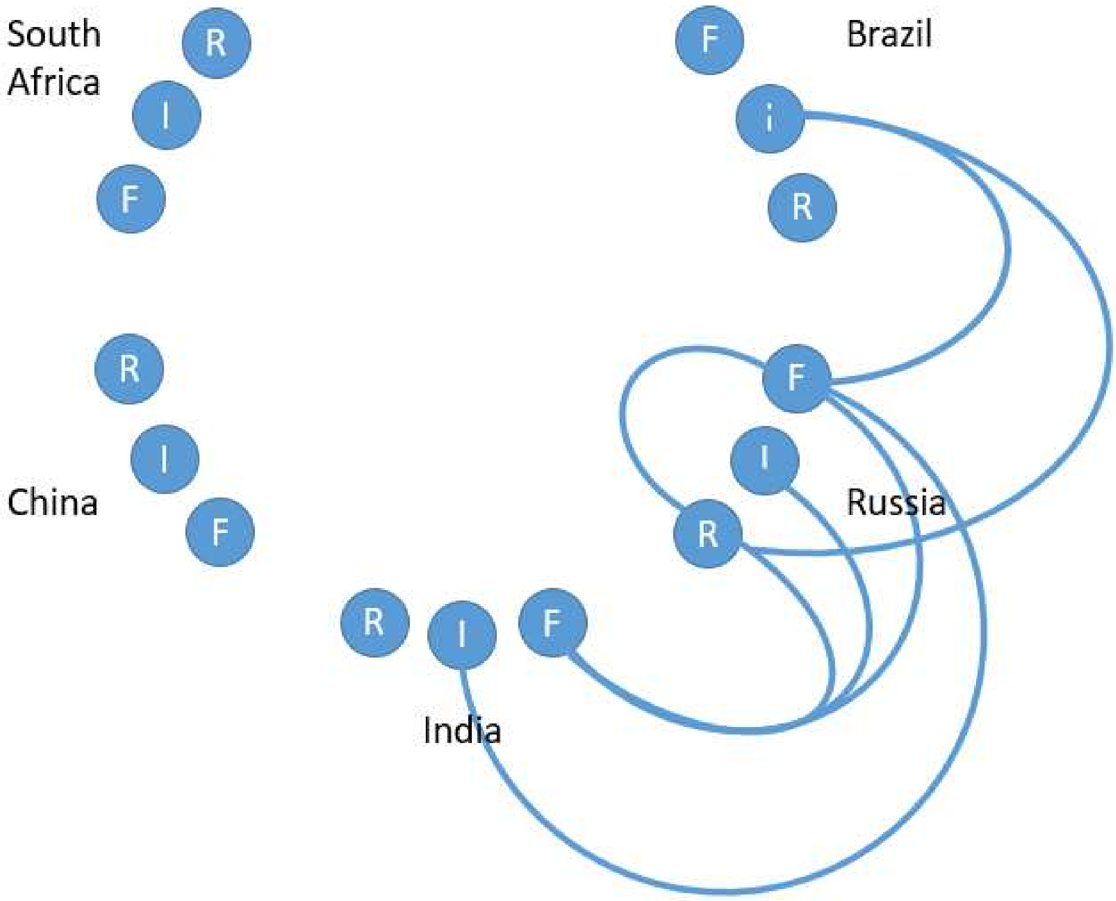


Figure 3: Russian network diagram

Figure 3 illustrates all the interdependence and contagion events associated with Russia. Interdependence is observed between Russia's financial and resource sectors. All of Russia's sectors seem to have a considerable amount of interdependence cohorts. This is to be expected, since Russia's top exports are crude petroleum (28%) and refined petroleum (17%). These products are known to be volatile and can have spill-over effects to the economy as a whole. Russia and India seems to share a particularly unique relationship. All of Russia's sectors share interdependence with the Indian financial sector. In addition to this, Russia's financial sector shares interdependence with India's industrial sector. This is to be expected, since the relationship between Russia and India has grown since the Cold War (Bhaskar, 2019). In addition, continuous efforts have been initiated to further strengthen ties between these two countries. An example of this is their commitment to increase bilateral trade to US$30 billion by 2025, up from the initial US$9.4 billion target for 2017 (Embassy of India Moscow, 2014).

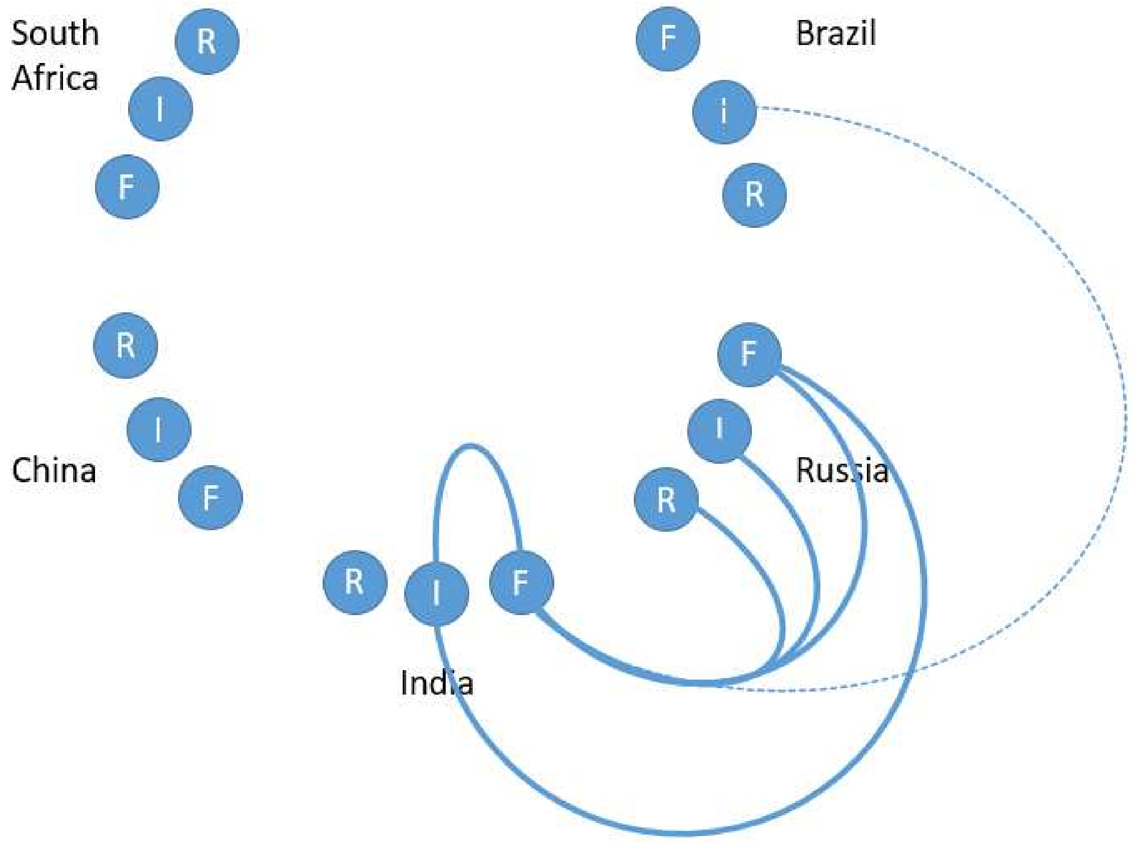


Figure 4: Indian network diagram

Figure 4 illustrates all the interdependence and contagion events associated with India. Interdependence was observed between India's financial and industrial sectors. Most of the relationships were concentrated in the Brazilian and Russian sectors. As previously stated, this may be a result of India and Russia's continuous efforts to strengthen their bilateral relationship. Adding to this, India's main import category is raw mineral products, such as crude oil (18%) and coal briquettes (4.7%), and these are also some of the main Brazilian and Russian exports.

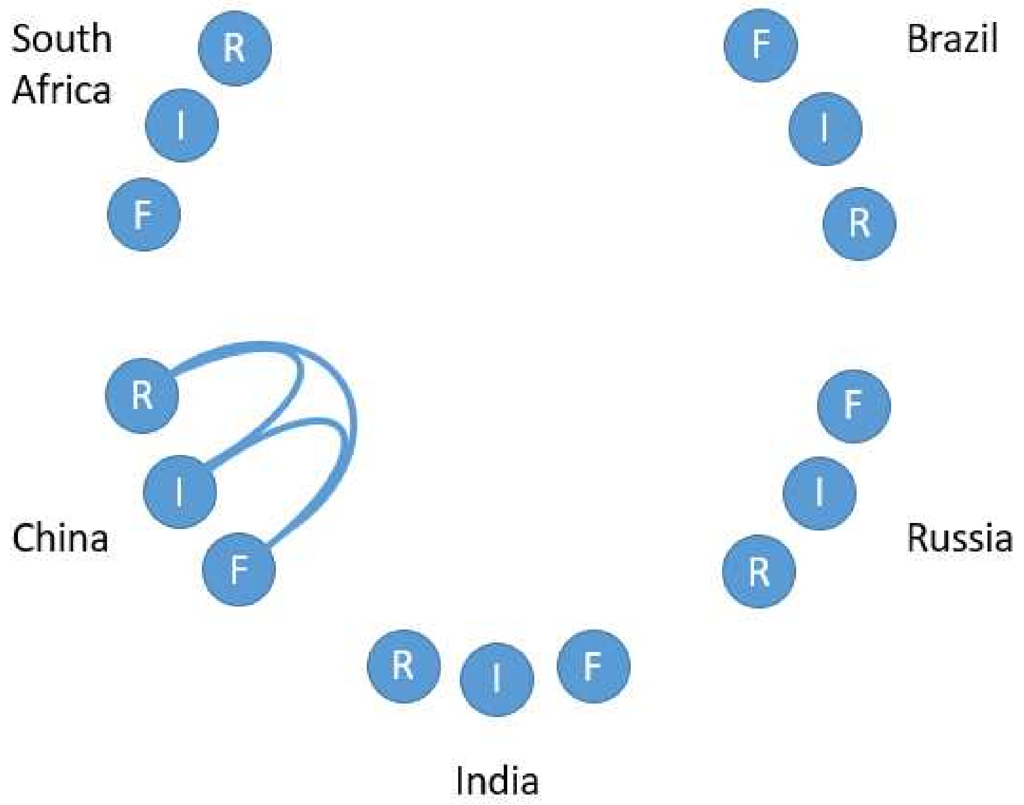


Figure 5: Chinese network diagram

Figure 5 illustrates all the interdependence and contagion events associated with China. China's economy seems to be the most integrated since all of its sectors experienced interdependence with the other in-country sectors. Apart from South Africa, China is also the most independent country within the BRICS grouping. This is interesting since China is the largest exporter in the world, and it may be explained by the fact that the tail dependence coefficients might fail to detect contagion or interdependence if the relationship is unidirectional (Joe, 1997).

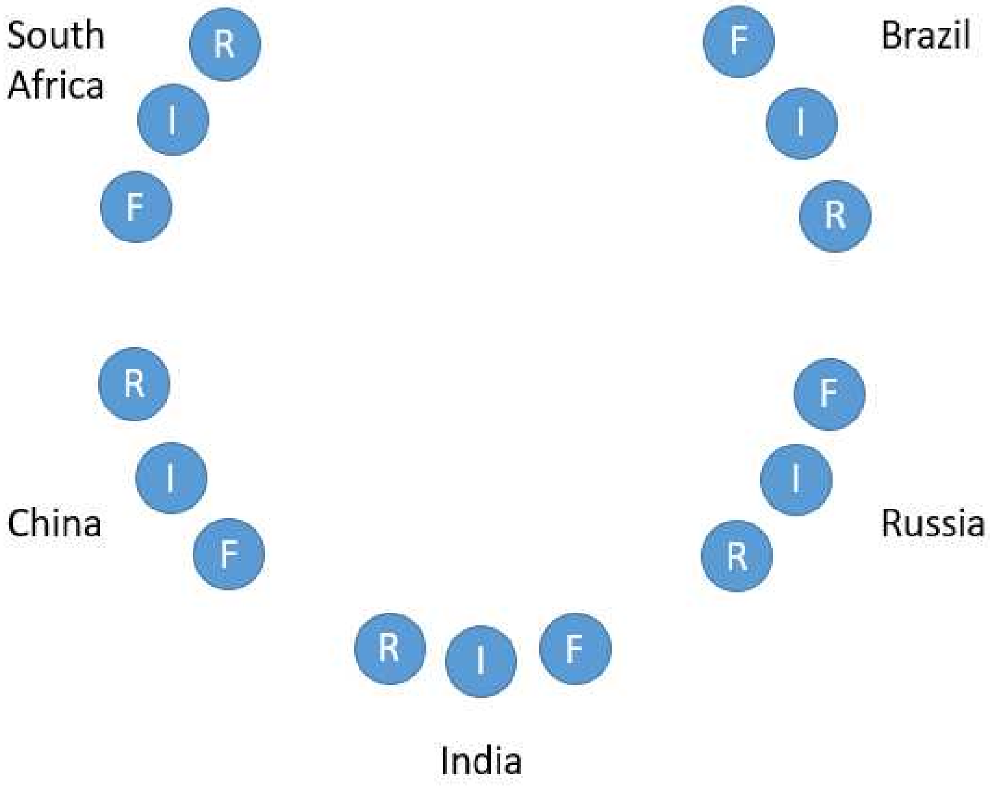


Figure 6: South African network diagram

Figure 6 illustrates all the interdependence and contagion events associated with South Africa. As stated before, no interdependence or contagion events are observed with South Africa. This further supports other researchers' findings that question including South Africa within the BRICS grouping.

The results from Figures (2) to (6) show that in most cases, interdependence rather than contagion was observed. Interdependence between different countries' sectors can be explained by their continuous efforts to align their economic policies. The most notable example of this is between Russia and India. On the other hand, interdependence within a country's sectors was observed between Brazil's financial and industrial sectors, Russia's financial and resource sectors, India's financial and Industrial sectors and China's financial, industrial, and resource sectors. Except in the case of China's resource and industrial sectors, within country interdependence is only observed where the financial sector of a country is involved. These results indicate that the BRICS countries' financial sectors play a critical role in the growth of other sectors within country. Similar findings were noted by Ariq (2016) and Mugova (2017), who established that growth in the financial sector leads to growth in other sectors within the BRICS context. From an investor's perspective, it follows that the effects of diversification may be limited if investment is made in the financial sector and another sector in the same country.

China, however, seems to be the exception in the different countries' contagion effects. As previously stated, this may be because the tail dependence coefficients are limited to relationships that are bidirectional and might fail to identify relationships that are unidirectional (Joe, 1997). This study's results are in line with Ahmad, Mishra and Daly's (2018) findings that established that the BRIC countries are a heterogeneous asset class and that China can provide additional opportunities for diversification within this grouping.

Section 5 Conclusion

This study sought to present a new approach to distinguish between contagion and interdependence. An R-Vine Copula approach was considered to estimate the dependence structures and bivariate Copulae between the estimated volatility of different markets. Thereafter, the tail dependence coefficients were estimated and a simulation procedure was used to determine their levels of significance. By considering the upper and lower tail dependence coefficients simultaneously, this study distinguished between contagion and interdependence. In doing so, this study extended Cubillos-Rocha et al.'s (2019) study, which only focussed on identifying contagion when tail dependence analysis was applied.

Another important contribution of this study was to identify contagion and interdependence structures at sectorial rather than the aggregated level of stock exchanges. Thus, the study analysed the contagion and interdependence structures of the BRICS countries' financial, industrial, and resource sectors.

This study's results established that there is limited evidence of contagion and interdependence in the co-movement between the different BRICS countries' sectors. The different sectors of the South African and Chinese stock exchange markets, for example, experienced no contagion or interdependence events with any of the other sectors within BRICS. Brazil's resource sector experienced the same, with no contagion or interdependence with or between other sectors. This indicates that the BRICS nations can be considered as offering diverse investment opportunities if careful consideration is taken. This result is aligned to Ahmad et al.'s (2018) study that established that the BRICS nations can be considered as a heterogeneous asset class. This has clear implications for hedge fund managers who construct BRICS-focussed investment funds (Sundaram, 2012).

In most cases where strong co-movement was observed between the considered sectors, the researcher could not find evidence of contagion, but rather of interdependence. This is in line with Forbes and Rigobon's (2002) findings that suggest that strong market co-movements during periods of financial shock may be a continuation of strong cross-market linkages, i.e. interdependence instead of contagion. The most notable case is the interdependence of the Russian and Indian sectors. From an investor's perspective, it suggests that investors should proceed with caution when investing in Russia and India. This is due to normal portfolio optimisation techniques relying heavily on traditional correlation estimates that could fail to detect the relationships between assets that the suggested technique can identify. Policy-makers should also be aware that their continuous efforts to co-align Russian and Indian economic policies are bearing fruit (Bhaskar, 2019).

Within country interdependence is also studied where it is found that, in most cases, interdependence mainly exists with the financial sector within the same country. This finding is supported by Ariq (2016) and Mugova's (2017) observations. The latter studies identified that growth in the financial sector leads to growth in other sectors within the BRICS context. From a portfolio optimisation perspective, it suggests that investing in the financial sector and another sector within the same BRICS country may leave a portfolio over-exposed. Policy-makers should also act with a heightened sense of caution if they consider making fundamental changes in the structure a BRICS country's financial sector.

The question as to whether or not South Africa should be in the BRICS grouping is also addressed in this study. As in Smith (2013), Davies (2013) and Anuoluwapo et al. (2018), it was established that caution should be used if South Africa is considered to be similar to its cohorts in the BRICS grouping. South Africa failed to provide any significant bidirectional relationship with any other country. This should indicate to practitioners and policy-makers alike that South Africa should not be considered part of the BRICS grouping. However, other researchers, like Bonga-Bonga (2017) have found that although South Africa does not have a significant effect on the other BRICS nations, countries like India and China affect South Africa significantly.

To build on this study, future researchers should consider extending the suggested methodology to incorporate methods of exposing unidirectional relationships. One method would be to develop a conditional tail dependence coefficient estimator or changing the simulation technique to incorporate flexible conditional distributions. Different methods to fit the Copula's marginals should also be considered in order to better isolate the shocks in the different markets.

This study’s outcomes are expected to add to the current discussion of how shock spill-overs are quantified. Moreover, the results should be of considerable interest to international investors who are considering methods of diversifying their current portfolio with assets in emerging markets. Finally, this should also be of interest to policy-makers who focus on the effects of their continuous efforts to align the BRICS economies.

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Appendix A

Table A1: Fitted Copulas using the R-vine Copula technique

Indices	*Copula*	*Par 1*	*Par 2*
Brazil Financials and Brazil Industrials	Rotated Bb8 Copula (180 Degrees; “survival Bb8”)	3.0095	0.3841
Brazil Financials and Brazil Resources	Rotated Bb8 Copula (180 Degrees; “survival Bb8”)	2.4331	0.5816
Brazil Financials and China Financial	Independence Copula	0.0000	0.0000
Brazil Financials and China Industrial	Tawn Type 1 Copula	1.8455	0.0023
Brazil Financials and China Resource	Bb8 Copula	1.6059	0.9223
Brazil Financials and India Financial	Tawn Type 1 Copula	1.1019	0.0695
Brazil Financials and India Industrials	Frank Copula	1.1994	0.0000
Brazil Financials and India Resources	Rotated Tawn Type 2 Copula (270 Degrees)	-1.3850	0.1014
Brazil Financials and Russia Financial	Rotated Clayton Copula (270 Degrees)	-0.1226	0.0000
Brazil Financials and Russia Industrial	Bb8 Copula	3.1092	0.5567
Brazil Financials and Russia Resources	Rotated Bb8 Copula (270 Degrees)	-1.8932	-0.7586
Brazil Financials and South Africa Financial	Rotated Bb8 Copula (270 Degrees)	-1.2404	-0.9609

Table A1 continues on the next page

Table A1 continued

Brazil Financials and South Africa Industrial	*Rotated Tawn Type 2 Copula (270 Degrees)*	*-3.8491*	*0.0031*
Brazil Financials and South Africa Resource	Bb8 Copula	1.6230	0.9902
Brazil Industrials and Brazil Resources	Rotated Tawn Type 2 Copula (270 Degrees)	-1.3102	0.1878
Brazil Industrials and China Financial	Rotated Clayton Copula (180 Degrees; “survival Clayton”)	0.1046	0.0000
Brazil Industrials and China Industrial	Rotated Bb8 Copula (90 Degrees)	-1.1214	-0.9303
Brazil Industrials and China Resource	Rotated Tawn Type 1 Copula (90 Degrees)	-1.3138	0.0598
Brazil Industrials and India Financial	Tawn Type 2 Copula	1.4222	0.0560
Brazil Industrials and India Industrials	Rotated Bb8 Copula (270 Degrees)	-1.3157	-0.7770
Brazil Industrials and India Resources	Rotated Bb8 Copula (90 Degrees)	-1.2592	-0.9602
Brazil Industrials and Russia Financial	Rotated Tawn Type 2 Copula (90 Degrees)	-2.2610	0.0121
Brazil Industrials and Russia Industrial	Student T Copula (t-copula)	-0.0517	10.8311
Brazil Industrials and Russia Resources	Student T Copula (t-copula)	-0.0088	14.8672

Table A1 continues on the next page

Table A1 continued

Brazil Industrials and South Africa Financial	*Rotated Tawn Type 2 Copula (270 Degrees)*	*-1.2321*	*0.0590*
Brazil Industrials and South Africa Industrial	Rotated Tawn Type 1 Copula (180 Degrees)	1.3025	0.1739
Brazil Industrials and South Africa Resource	Bb6 Copula	1.3988	1.8963
Brazil Resources and China Financial	Tawn Type 2 Copula	1.3715	0.3150
Brazil Resources and China Industrial	Rotated Tawn Type 2 Copula (180 Degrees)	1.1567	0.1953
Brazil Resources and China Resource	Rotated Bb8 Copula (180 Degrees; “survival Bb8”)	1.3920	0.9399
Brazil Resources and India Financial	Tawn Type 1 Copula	1.1972	0.2221
Brazil Resources and India Industrials	Rotated Tawn Type 2 Copula (90 Degrees)	-1.9879	0.0475
Brazil Resources and India Resources	Rotated Clayton Copula (180 Degrees; “survival Clayton”)	0.1077	0.0000
Brazil Resources and Russia Financial	Bb8 Copula	1.9016	0.7063
Brazil Resources and Russia Industrial	Rotated Clayton Copula (90 Degrees)	-0.1012	0.0000
Brazil Resources and Russia Resources	Rotated Tawn Type 1 Copula (180 Degrees)	1.2416	0.2636

Table A1 continues on the next page

Table A1 continued

Brazil Resources and South Africa Financial	*Rotated Tawn Type 2 Copula (90 Degrees)*	*-1.5964*	*0.0524*
Brazil Resources and South Africa Industrial	Rotated Joe Copula (90 Degrees)	-1.0649	0.0000
Brazil Resources and South Africa Resource	Tawn Type 2 Copula	2.7054	0.7461
China Financial and China Industrial	Student T Copula (t-copula)	-0.0044	20.7446
China Financial and China Resource	Clayton Copula	0.0798	0.0000
China Financial and India Financial	Rotated Tawn Type 1 Copula (270 Degrees)	-1.5188	0.1240
China Financial and India Industrials	Rotated Clayton Copula (90 Degrees)	-0.1034	0.0000
China Financial and India Resources	Rotated Tawn Type 1 Copula (270 Degrees)	-1.1557	0.1303
China Financial and Russia Financial	Frank Copula	0.6185	0.0000
China Financial and Russia Industrial	Student T Copula (t-copula)	0.0035	12.3063
China Financial and Russia Resources	Rotated Joe Copula (270 Degrees)	-1.1161	0.0000
China Financial and South Africa Financial	Joe Copula	1.2250	0.0000

Table A1 continues on the next page

Table A1 continued

China Financial and South Africa Industrial	*Rotated Bb8 Copula (180 Degrees; "survival Bb8")*	*1.8171*	*0.8595*
China Financial and South Africa Resource	Bb8 Copula	6.0000	0.7733
China Industrial and China Resource	Rotated Joe Copula (90 Degrees)	-1.0530	0.0000
China Industrial and India Financial	Clayton Copula	0.0886	0.0000
China Industrial and India Industrials	Tawn Type 1 Copula	1.3985	0.1070
China Industrial and India Resources	Rotated Tawn Type 1 Copula (270 Degrees)	-2.0227	0.0442
China Industrial and Russia Financial	Rotated Tawn Type 2 Copula (90 Degrees)	-2.9211	0.0049
China Industrial and Russia Industrial	Rotated Bb8 Copula (90 Degrees)	-1.4563	-0.7597
China Industrial and Russia Resources	Rotated Joe Copula (90 Degrees)	-1.0876	0.0000
China Industrial and South Africa Financial	Rotated Tawn Type 2 Copula (270 Degrees)	-1.9662	0.0988
China Industrial and South Africa Industrial	Rotated Bb8 Copula (180 Degrees; "survival Bb8")	1.7299	0.6439
China Industrial and South Africa Resource	Frank Copula	5.6369	0.0000

Table A1 continues on the next page

Table A1 continued

China Resource and India Financial	*Tawn Type 1 Copula*	*1.0590*	*0.2220*
China Resource and India Industrials	Gaussian Copula	0.0958	0.0000
China Resource and India Resources	Clayton Copula	0.3721	0.0000
China Resource and Russia Financial	Rotated Bb8 Copula (180 Degrees; "survival Bb8")	1.6797	0.6494
China Resource and Russia Industrial	Gaussian Copula	0.0607	0.0000
China Resource and Russia Resources	Gaussian Copula	0.2264	0.0000
China Resource and South Africa Financial	Rotated Tawn Type 2 Copula (90 Degrees)	-1.4861	0.1415
China Resource and South Africa Industrial	Rotated Tawn Type 1 Copula (180 Degrees)	1.9718	0.0877
China Resource and South Africa Resource	Bb7 Copula	1.8713	0.0651
India Financial and India Industrials	Rotated Tawn Type 2 Copula (90 Degrees)	-1.5898	0.0272
India Financial and India Resources	Rotated Clayton Copula (270 Degrees)	-0.1472	0.0000
India Financial and Russia Financial	Rotated Bb8 Copula (180 Degrees; "survival Bb8")	1.1684	0.9958

Table A1 continues on the next page

Table A1 continued

India Financial and Russia Industrial	*Tawn Type 2 Copula*	*1.2736*	*0.0703*
India Financial and Russia Resources	Rotated Bb7 Copula (180 Degrees; “survival Bb7”)	1.0029	0.0853
India Financial and South Africa Financial	Rotated Tawn Type 2 Copula (180 Degrees)	1.7932	0.0417
India Financial and South Africa Industrial	Bb6 Copula	1.1235	1.0944
India Financial and South Africa Resource	Bb7 Copula	1.9515	0.3373
India Industrials and India Resources	Frank Copula	-1.8445	0.0000
India Industrials and Russia Financial	Bb8 Copula	1.4065	0.7076
India Industrials and Russia Industrial	Bb8 Copula	1.2664	0.9488
India Industrials and Russia Resources	Rotated Tawn Type 1 Copula (180 Degrees)	1.1130	0.1866
India Industrials and South Africa Financial	Rotated Tawn Type 2 Copula (180 Degrees)	1.1940	0.2668
India Industrials and South Africa Industrial	Rotated Bb7 Copula (180 Degrees; “survival Bb7”)	1.1638	0.4057
India Industrials and South Africa Resource	Bb8 Copula	2.3568	0.9900

Table A1 continues on the next page

Table A1 continued

India Resources and Russia Financial	*Rotated Joe Copula (270 Degrees)*	*-1.0236*	*0.0000*
India Resources and Russia Industrial	Tawn Type 2 Copula	1.6667	0.0735
India Resources and Russia Resources	Bb8 Copula	1.7974	0.6012
India Resources and South Africa Financial	Rotated Tawn Type 2 Copula (180 Degrees)	1.2932	0.0999
India Resources and South Africa Industrial	Rotated Tawn Type 2 Copula (180 Degrees)	1.9036	0.0155
India Resources and South Africa Resource	Bb6 Copula	1.4408	1.7785
Russia Financial and Russia Industrial	Clayton Copula	0.1710	0.0000
Russia Financial and Russia Resources	Rotated Bb8 Copula (180 Degrees; "survival Bb8")	1.2559	0.7874
Russia Financial and South Africa Financial	Tawn Type 2 Copula	1.7187	0.0464
Russia Financial and South Africa Industrial	Gaussian Copula	0.3152	0.0000
Russia Financial and South Africa Resource	Bb1 Copula	0.0637	1.7082
Russia Industrial and Russia Resources	Rotated Tawn Type 1 Copula (270 Degrees)	-2.2252	0.0157

Table A1 continues on the next page

Table A1 continued

Russia Industrial and South Africa Financial	*Joe Copula*	*1.0674*	*0.0000*
Russia Industrial and South Africa Industrial	Rotated Tawn Type 1 Copula (180 Degrees)	1.2733	0.1409
Russia Industrial and South Africa Resource	Bb8 Copula	6.0000	0.5564
Russia Resources and South Africa Financial	Gaussian Copula	0.0890	0.0000
Russia Resources and South Africa Industrial	Rotated Tawn Type 1 Copula (180 Degrees)	1.6299	0.1454
Russia Resources and South Africa Resource	Bb8 Copula	2.5659	0.7892
South Africa Financial and South Africa Industrial	Gaussian Copula	-0.1595	0.0000
South Africa Financial and South Africa Resource	Rotated Bb8 Copula (270 Degrees)	-6.0000	-0.6678
South Africa Industrial and South Africa Resource	Bb8 Copula	5.1254	0.8279