**Sectoral dependence and contagion in the BRICS grouping: an application of the R-vine copulas**

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# **Chapter 1 Introduction**

## **Background and problem statement**

The minimum variance portfolio theory introduced by Markowitz (1952) had a major effect on how portfolio allocation is considered. The main pivot in ideology was that a portfolio should not only maximize future individual asset returns, but also minimize the correlations between said assets. Since then, methods based on asset correlation for portfolio selection have gained prominence in the financial economic literature (see 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, time-varying correlation portfolio allocation strategies have been considered by Campbell, Koedijk and Kofman (2002). The latter authors focus on developing an estimator for correlation that considers the different states of the market. This allows a practitioner to use an amended variance-covariance matrix for mean-variance portfolio optimization that incorporates the additional downside risk during turmoil market regimes.

In addition, still in the context of rebalancing portfolios, studies attempted to uncover the extent to which correlations of asset returns increase during turmoil market regimes (see Graflund & Nilsson (2002); Pelletier (2006); Ang & Bekaert (2002) and 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 literature abounds in distinguishing between contagion and interdependence, especially in the context of portfolio allocation, there is however, no consensus in terms of the methodology to be 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 criticized by Forbes & Rigonon (2002) who proved that relying on the correlation estimate to distinguish between contagion and interdependence without addressing the issue of heteroscedasticity 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 & Rigonon (2002) and others (see Boyer, Gibson, & Loretan (1999) and Loretan & English (2000)) continue to study unbiased estimators of the correlation structures but Corsetti, Pericoli, & Sbracia (2005) prove that these estimators have too stringent assumptions.

Still 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 Heteroscedasticity (GARCH) type models (see Bonga-Bonga (2018) and Akhtaruzzaman & Shamsuddin (2018)). By using these techniques, these studies are able to distinguish between contagion and interdependence.

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

This study contributes to the line of literature on how to identify and distinguish between contagion and interdependence by applying an R-vine copula methodology. Given that contagion is in general 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 study 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 there is contagion or interdependence in the transmission of shocks between markets or economies. It is worth noting that past studies made use of extreme value theory to identify the existence of contagion (see Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia (2019)). However, they did not go further to distinguish between contagion and interdependence using the theory. Thus, this study proposes to distinguish between contagion and interdependence with the aid of extreme value theory, and the R-Vine Copula, by assessing the extent of shocks transmission between different sectors of BRICS stock exchanges, namely the Financial, Industrial and Resource sectors. The study of the BRICS countries, i.e. Brazil, Russia, India, China and South Africa, is of great importance for investors and asset managers since the BRICS grouping consists of 5 major emerging economies that provide 23.2% of the world GDP as of April 2018 (IMF, 2018). The importance of conducting a study among the BRICS economies also result from the fact that compared to developed economies, emerging markets provide a higher return on capital (Henry, 2007) and are important hubs for international portfolio diversification.

The 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 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 finds its growth in the exporting of 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 is also the largest exporter of platinum in the world (Workman, 2019).

## **Research question**

This study provides a contribution to the literature that identifies and distinguishes between contagion and interdependence in shocks transmission by applying the R-Vine methodology. With this methodology, the study will be able to test the extent of correlation between the extreme joint distribution of the different sectors of the BRICS stock exchanges. Thus, the study aims at providing answers to the following questions:

* How can one distinguish between contagion and interdependence by modelling the extreme joint distribution of different assets?
* How do the extreme joint distributions of the different sectors of BRICS stock exchanges correlate?
* How can one distinguish between interdependence and contagion from the transmission of shocks between the different sectors of BRICS stock exchanges?

## **Research methodology**

To study the contagion effects between the sectors of the BRICS countries, the study will make use of the regular vine methodology as suggested by Cubillos-Rocha, Gomez-Gonzalez and Melo-Velandia (2019). The authors assessed exchange rate contagion between different regions of the world. The tail dependence coefficients will be considered to measure the extent of tail dependence between the different indices. Unlike their study, this study uses the fitted variances of each series as the marginal models and proposes a way of distinguishing between contagion and interdependence based the magnitude of tail dependence between markets or economies. For example, if it is found that only the upper tail dependence coefficient between the variances of the markets is significant, then it could be concluded that contagion occurs between these markets. On the other hand, if the lower and upper tail dependence coefficient are both significant, then interdependence rather than contagion is observed between the two markets.

Daily data over the period of January 2006 to May 2019 is used in this study. The sample includes periods of major crises, necessary for differentiating the magnitude of shocks transmission. Returns of the different sectors of BRICS stock exchanges are computed using indices registered on the São Paolo Stock Exchange (BOVESPA) for Brazil, Moscow Exchange (MOEX) for Russia, the National Stock Exchange of India (NSE) for India, the Shanghai Stock Exchange (SSE) for China and the Johannesburg Stock Exchange (JSE) for South Africa.

## **Importance of the study**

The analysis of the relationships between different financial assets are of integral importance in portfolio optimisation. This is due to the typical goal of diversification, which is to use the correlations of different assets to minimise the risk of an investment portfolio. Given that contagion implies significant correlation during turmoil periods and interdependence that assets have strong correlation, be it in turmoil or tranquil periods, asset managers and investors should be able to identify whether correlations are the result of contagion or interdependence. Such insight will lead the asset manager or investor to different 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 mould policies in a pre-emptive fashion.

It is important to note that very few studies have considered the co-movement of the BRICS stock exchanges at a sector level. Such an insight is of great value for asset allocation and portfolio selection among BRICS countries. Asset managers may realise that a combination of assets in the resource sector in South Africa may be a good combination with assets in the Industrial sector of the Chinese economy for optimal portfolio allocation during crisis periods. Such an insight could be formed from the analysis of the dependence structure between the two sectors in the context of extreme value theory.

## **Structure of the study**

The remainder of the study is structured as follows: Chapter two presents the literature review on the evolution of contagion models. Chapter three presents the econometric technique used in the study, namely, the regular vine copula methodology with the estimation and simulation of tail dependence coefficients. Chapter four presents the data and conducts the econometric estimation. Lastly, Chapter five presents the conclusion of the study and policy implications derived from the results.

# Chapter 2 Literature Review

There has been a wide array of authors that have developed models to distinguish between interdependence and contagion. Initial studies on the subject focussed on testing whether correlations increased after economic shocks, with the seminal paper of King & Wadhwani (1990) introducing this line of literature. Using hourly stock market data from the New York, Hong Kong and London stock exchanges before and after the October 1987 US stock market crash, the authors studied what the effect of an idiosyncratic shock in one market will be on another market, and how this shock will affect the correlation structure of the two markets. The authors found increases in correlation after the stock market crash and concluded that there in fact exists contagion between the markets rather than interdependence. This line of work was extended by Lee & Kim (1993) who considered the weekly returns of 12 stock markets over the October 1987 crash. The authors also considered whether significant changes in correlation is observed after the crash. The literature was extended by incorporating a factor analysis component, which in turn is used to measure the relative importance before and after the crash of domestic and international factors in the investment decision making process.

Later studies, however, have revealed that focussing solely on changes in correlation might lead to ambiguous results. A prominent paper by Forbes & Rigobon (2002) proves that a correlation estimate is biased and is in fact conditional on the variance of the market that provides the initial shock. This leads to the finding that heteroscedasticity in market indices will naturally lead to higher correlations during a financial crisis. Hence, solely studying 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 exogeneous global shocks and no feedback from the market that did not initially experience the shock. This methodology is tested by considering contagion between the financial markets of 28 countries during the US stock market crash of 1987, the Mexican Peso crisis of 1994 and the East Asian crisis of 1997. A Vectorised Auto Regression (VAR) model is applied to tranquil and turbulent periods to consider the changes in the variance-covariance structure. Short term interest rates of the US, country in crisis and corresponding country are also included for control variables. After applying the correction factor to the calculated correlations, it is shown that no contagion effect was truly present, but rather interdependence of the market indices. Others like Boyer, Gibson, & Loretan (1999) and Loretan & English (2000) have also considered correcting for the bias in the correlation measure but Corsetti, Pericoli, & Sbracia (2005) show that the supposed results of these improvements are not realistic since too stringent and unrealistic assumptions are made regarding the variance of the country-specific shocks.

To circumvent these issues, multiple regression techniques have also been considered. This line of literature of discerning between interdependence and contagion using regression was introduced by Horen, Jager, & Klaassen (2006). The authors considered studying the existence of contagion effects during the Asian crisis of 1997 from the origin of the crisis, the exchange market of Thailand, to the exchange markets of the Philippines, Indonesia, Malaysia and Korea. The authors follow the work of Girton & Roper (1977) by constructing an Exchange Market Pressure (EMP) variable as the response variable which is a function of the change in exchange rate, the change in interest rate and money supply for each country. This is necessary since the bulk of the exchange rates that are considered are pegged against the US dollar. Finally, the authors model the EMP of a country by considering a set of macro-economic factors and the EMP of Thailand. To find the degree to which contagion takes place, the authors also add a variable that is equal to zero in tranquil periods and equal to the EMP of Thailand in crisis periods. The coefficient of this variable indicates the degree of contagion from Thailand to other countries. If this state variable is significant, contagion is present. If not, only interdependence is observed. Evidence of contagion is found from Thailand to Indonesia and Malaysia, whereas interdependence is observed between Thailand and Korea and the Philippines. In line with this methodology, Billio, Duca, & Pelizzon (2005) incorporate endogenous regime switching by using Markov switching Error Correction Models. By doing this, the authors provide a way to ensure that the crisis periods are endogenously defined instead of arbitrarily by the researcher. Moreover, by considering the estimated coefficient of the error correction term, the authors can directly test whether investors ignore economic fundamentals during times of economic crisis. The authors continue by discerning between contagion and interdependence for the European stock market, 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 crisis periods. By utilizing time-varying quantile regression, Ye, Luo, & Liu (2017) studied contagion and interdependence between Asian, US, and European equity markets during the 2007-2009 US banking crisis and during the 2010 Greek sovereign bonds downgrading. The authors make use of the quantile-specific odds ratio (qor) that indicates the odds of two return indices simultaneously being below specified quantiles. This method has the added advantage of a clear interpretation since 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. The Greek sovereign bonds downgrading, in comparison, did not have such a strong contagion effect on the other markets, indicating that Greece may play a much more subdued role in the global economy. By utilizing quantile regression, Lyocsa & Horvath (2018) also considered contagion from the US equity market to the equity markets of 6 developed countries. The authors also incorporate a wide array of control variables that consider 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 can test for contagion following the definition provided by Bekhaert, Harvey, & Ng (2005). The methodologies of Billio, Duca, & Pelizzon (2005) and Ye, Luo, & Liu (2017) were combined by Ye, Zhu, Wu, & Miao (2016) who consider a Markov regime-switching quantile regression model to detect financial contagion. The authors continue to use this technique to consider changes in financial contagion, estimated through the quantile regression component, throughout different Markov states, i.e. different periods of financial shock.

Correlation analysis is also circumvented by authors like Bekhaert, Harvey, & Ng (2005). A two-factor asset pricing model of the excess return of a country is used to detect interdependence and contagion between the regions of Europe, Latin America and Southeast Asia. The two factors are the regional equity portfolio return and the U.S. equity market return. The estimated coefficients of the model are 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 are also included in the two-factor model. This is expanded by modelling the idiosyncratic shocks with a Generalised Auto Regressive Conditional Heteroscedasticity (GARCH) model with asymmetry. Overall and period specific contagion is then identified by studying the relationship of the residuals of different markets. The authors found that the Mexican Peso crisis (1994) did not provide a significant surge in contagion between markets. The Asian crisis (1997), however, shows clear evidence of being a contagious event, especially within the Oceanic countries. The use of GARCH-type models can be seen by a variety of authors. A VAR-DCC-GARCH model is 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 main findings from the author is that there exists capital market interdependence between Brazil and South Africa and that the contagion effect of crises originating from Russia, India and China on South Africa is greater than the contagion effect of crises originating in South Africa on said countries. A DCC-GARCH model was used by Akhtaruzzaman & Shamsuddin (2018) to measure interdependence and contagion between the US and other developed, emerging and frontier economies. The main contribution is that the authors provide a disaggregated view by focussing on contagion between financial and non-financial firms. By using a Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) model, Kenourgios & 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. The inaugural study by Costinot, Roncalli, & Teiletche (2000) use Normal and Extreme Value copulas to study interdependence and contagion during the Asian Crisis between the stock and exchange markets of Thailand, Korea, Malaysia, Philippines and Indonesia. It is found 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, Mathieson, & Yao (2004) used Extreme Value Theory measures whilst utilizing copulas. Specifically, they developed contagion measures for the bottom and top 5 percent returns, hence defining bear and bull market contagion respectfully. By studying the weekly stock market returns of a wide array of mature and emerging economies, the main findings of the authors are that there is a significant difference in the contagion patterns across regions. Also, contagion is higher for negative returns, i.e. during bear markets. A mixed copula approach is considered by Hu (2006) to take account for various patterns of dependence structures. The authors consider a Gaussian copula with no tail dependence, Gumbel copula with positive right tail dependence and its survival counterpart with positive left tail dependence. By considering the weights of the mixture model, the author can ascertain whether contagion exists and whether it is more prominent during positive or negative shocks. The authors study contagion between the S&P 500, FTSE, Nikkei and Hang Seng markets. The main finding is that only left tail dependence is observed, indicating that markets are expected to depreciate together instead of appreciate together. A mixed copula approach with Markov switching parameters is used by Rodriguez (2007) 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 become endogenous to the model. In studying multivariate dependence structures, Chollete, Heinen, & Valdesogo (2009) expands on this by doing a comparison between mixture copula models and canonical vine copulas. The authors find that canonical vine copulas will generally outperform mixture copulas since the latter implicitly limits the feasible region of dependence between variables. The authors continue by utilizing a regime switching canonical vine copula methodology to study the dependence structures between the G5 countries and Latin American regions. The two main findings are that canonical vine copulas generally dominate alternative dependence structures and the choice of copula can have a significant effect in modelling international portfolio returns. The copula methodology is also used by Horta, Mendes, & Vieira (2010) to test for interdependence and contagion from the US stock market to the stock markets of the Netherlands, Belgium, France and Portugal during the US subprime crisis of 2007 - 2009. Hypothesis tests based on the Kendall’s tau statistic are 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. The existence of interdependence and contagion between developed foreign exchange and stock markets to African stock markets was studied by Paul & Gideon (2017). The authors focussed on calculating the downside cumulative mean distribution Conditional Value-At-Risk (CoVaR) whilst using copula functions. They found that the effect of global shocks to African stock markets might only manifest post-crisis. Utilizing the flexibility of regular vine copulas, Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia (2019) studied contagion between developed and large developing economies whilst also considering whether 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 find that whilst contagion is more observable within countries of similar regions, emerging market currencies are more affected by developed market currencies. This study extends the techniques introduced by Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia (2019) since the regular vine copula methodology 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 article extends on this line of literature in a methodological manner by attempting to distinguish between interdependence and contagion. This is extremely relevant to an investor since one can follow different investment strategies in the case of interdependence or contagion. This study also focusses on interdependence and contagion on a disaggregated level, i.e. by considering the sectors of the BRICS countries. This is relevant since diversification strategies by modern investors can underestimate the correlation between different sectoral indices, whereby additional risk is unknowingly introduced into their portfolios.

# **Chapter 3 Methodology**

This study makes use of the R-vine copula approach to identify contagion and interdependence between the sectors in the BRICS countries. The regular vine copula approach first introduced by Joe (1997) 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 is done, the copula approach requires one to select the marginal models that will be used. In order to distinguish between contagion and interdependence, one needs to use a marginal model that will capture shocks and volatility in each series. This study considers fitting the first two moments of each series with an model with student t innovation distribution. This set of models are chosen since the time series in question can be serially dependent and have non-constant, extreme variances. Thereafter the variance of each series is predicted using the fitted models and used as the marginal models.

## 3.1 Model for the marginal distributions

After transforming the series into log-returns, the first two moments of each series are modelled using an model with student t innovation distribution with degrees of freedom. It follows that each series will have a parameter set . If the log-returns are defined as , with an indicator for the series and an indicator for time, the model can be defined as:

(1)

(2)

(3)

where follow a student t innovation distribution with degrees of freedom. The model specification is determined iteratively for each series by first fitting a range of models using the model specification , with . In alignment with Patton (2006), Jondeau & Rockinger (2006) and De Lira Salvatierra & Patton (2015), the BDS test is used to test the hypothesis that the models provide independent identically distributed residuals. The most parsimonious model which fails to reject the null hypothesis of the BDS test is finally chosen. In line with BanSaida (2018), if the null hypothesis is rejected for all model specifications, the model specification which provides the lowest absolute value of the BDS statistic is chosen. After the final model is estimated, the estimated variance of each series is determined which is then transformed to using the Probability Integral Transform (PIT). This will be 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 is an n-dimensional joint distribution function, with marginal distributions of the random variables , then there exists a unique copula function such that for all ,

. (4)

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

. (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 the extension by Joe (1996) who introduced the pair copula construction (PCC), allowing one to express the joint density function as a product of the marginal distributions and bivariate copulae, i.e.

(6)

with

(7)

where is the conditioning set of , is a variable contained in the set **,**  are the remaining elements and .

The usual representation of the PCC is that of nested trees , which are acyclical graphs with nodes and edges (Bedford & Cooke, 2001). The R-vine developed by Bedford & Cooke (2002) is represented by a nested set of trees , with a set of edges and nodes , where two nodes in tree are connected by one edge only if they share a common node in tree .

The R-vine copula that is used in this study is a general case of the PCC. It is represented as , with a vector of distribution functions, an n-dimensional R-vine and a set of bivariate copulas (Dißmann, Brechmann, & C. Czado, 2013).

To facilitate in the estimation procedure of Dißmann, Brechmann, & C. Czado (2013), the R-vine structure can be denoted as a lower triangular matrix .

The matrix is called an R-vine matrix if for and for all there is a in with

where

, and

.

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

. (8)

From this, Dißmann, Brechmann, & C. Czado (2013) propose the following estimation procedure for each tree in which is followed in this paper:

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 pick the tree structure where this is maximized.
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.
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 determined through the simulation procedure proposed by Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia (2019).

## 3.3 Tail Dependence Coefficients (TDC)

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 in terms of copulas developed by Joe (1997) is considered. If and are two series with corresponding cumulative distribution functions and respectively, the upper and lower tail dependence coefficients are defined as:

(9)

(10)

Note that the tail dependence coefficients are proven to be symmetric by Joe (1997), i.e.

and

To estimate equations (9) and (10), the empirical copula as defined by Deheuvels (1980) is used. This changes the expressions to

(11)

(12)

The following simulation exercise proposed by Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia (2019) is used to find the values for the TDC:

1. With the R-vine structure defined, simulate 10 000 observations of the variables utilizing the algorithms developed by Dißmann, Brechmann, & C. Czado (2013).
2. Calculate and 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.
5. Use the emperical distribution function of the TDCs for 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 in only the upper tail of the joint distribution, then contagion is observed. On the other hand, if there is significant dependence in both the upper tail and lower tail of the joint distribution, then interdependence is observed.

# **Chapter 4 Data and Results**

Daily data over the period of January 2006 to May 2019 is used in this study. This period is chosen as 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 on regional, financial and economic challenges (Info BRICS, 2019). The returns from the respective sectors are computed using indices registered on the São Paolo Stock Exchange (BOVESPA) for Brazil, Moscow Exchange (MOEX) for Russia, the National Stock Exchange of India (NSE) for India, the Shanghai Stock Exchange (SSE) for China and the Johannesburg Stock Exchange (JSE) for South Africa. The estimated variances for these returns will then be used to discern between contagion and interdependence between the relevant sector indices.

Table 1: Descriptive Statistics



Summary statistics for the daily index log returns of the sectors of the five BRICS countries are reported in Table 1. The mean levels are all close to 0 with India’s Industrial sector providing the lowest return level. Brazil provides the best overall return with all their sectors having positive returns. The highest standard deviation is observed in India’s Industrial sector, whereas Brazil’s Resource sector has the lowest standard deviation. Most indices display negative skewness, i.e. a long left tail, indicating that extreme negative returns have been observed. The indices with positive skewness are Brazil’s Financial and Resource sectors and India’s Financial and Resource sector. Most of the indices also display very high levels of kurtosis, most notably being Russia’s Industrial sector with 32.3498. This indicates that most series have very heavy tails and suffer from extreme outliers. The lowest kurtosis levels are observed with India’s Resource sector. However, most notably are the indices of the South African sectors which are markedly near normal, except for the Financial sector which has excess kurtosis of approximately 2. Finally, none of the Jarque-Bera test statistics were found to be significant, indicating substantial non-normality.

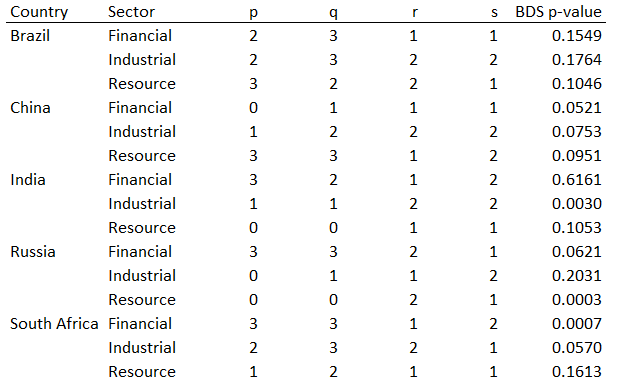
Table 2: Pearson correlation coefficients. The labels are shortened for brevity



The unconditional Pearson’s correlation coefficients are shown in Table 2. There are some cases where the positive correlations are high but this is mostly observed within country. Examples of this include the correlation between Brazil’s Industrial and Financial sectors with a correlation coefficient of and India’s Industrial and Financial sectors with a correlation coefficient of . Negative correlations, on the other hand, are rarely seen. The most negative correlation that is observed is again within country between Brazil’s Financial and Resource sector with a correlation coefficient of . Although these results do not seem to suggest the possibility of efficient portfolio selection by using the different BRICS assets, one needs to note the serious limitations of unconditional Pearson correlation coefficients in this setting (Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia, 2019). Moreover, while the dominating positive correlation between these assets may be indicative of sectoral co-movement in BRICS, possibly due to contagion, however, these correlations do not provide us with an indication as to whether correlations are different 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 high frequency of the data, significance tests become ever more questionable. Copula functions provide us with useful tools to overcome all these limitations of unconditional Pearson’s correlations.

The first step in the copula methodology is to find the appropriate marginal models for the different indices and use these marginals to filter the data. Hence, the first two moments of each series are modelled with an 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 the procedure described by BanSaida (2018), the parameter set for each marginal model is chosen such that the residuals are independent and identically distributed. If this cannot be achieved, the model with the smallest absolute BDS statistic is chosen. The results of the models for each series are reported in Table 3.

Table 3: Marginal model specification



All of the chosen models have some variation of the parameters, but it is interesting to note that India and Russia’s Resource sector consists of no mean equation.

Using the fitted variances attained from the specified models, the regular vine structure is estimated using the procedure described by Dißmann, Brechmann, & Czado (2013). The appropriate tree structure is found by maximizing the sum of the absolute Kendall taus. Since it is impractical to visualize the full set of 14 trees, only the first two are shown in Figure 1.

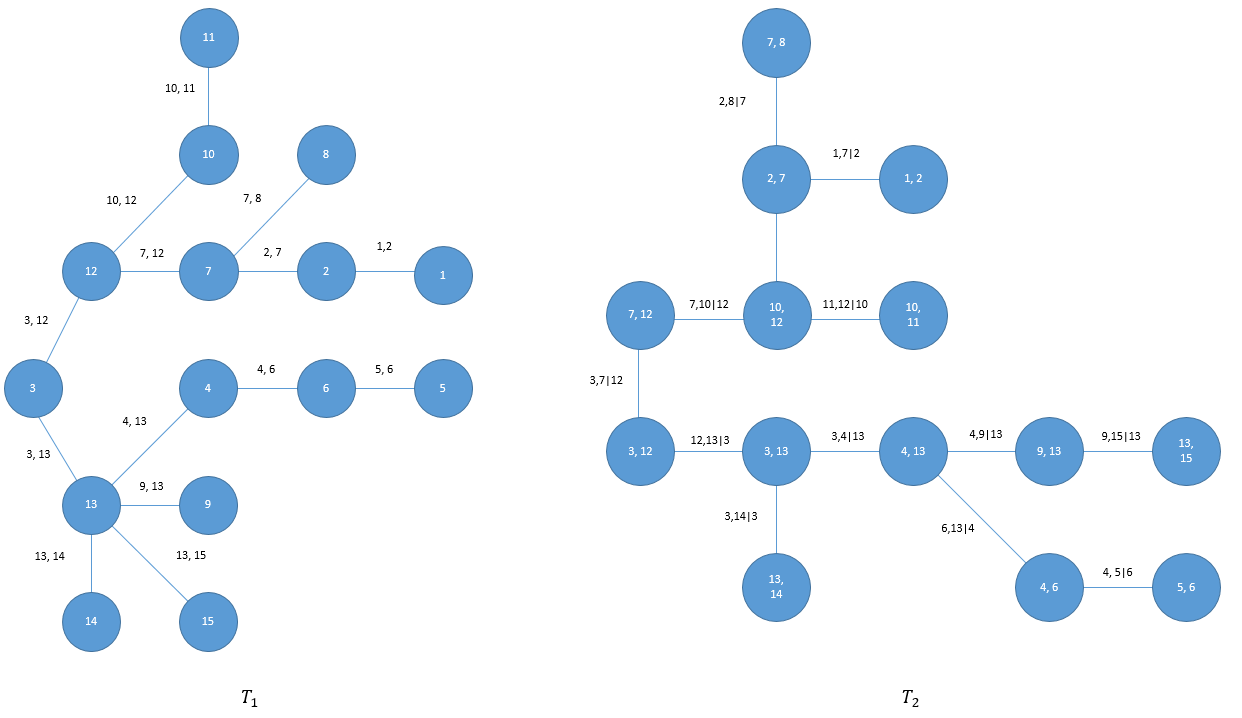
[[1]](#footnote-1)

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 () must be an edge in tree one (). As an example, one can consider node (10, 11) in tree two. Note that it is also an edge in tree one between the nodes (10) and (11). All further trees naturally follow 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 the parameters of each copula. Thirty-nine different copulas were considered for each bivariate copula specification. They are the Gaussian copula, the Student t copula (t-copula), the Frank copula, the Clayton copula (standard, rotated , and ), the Gumbel copula (standard, rotated , and ), the Joe copula (standard, rotated , and ), the BB1 copula (standard, rotated , and ), the BB6 copula (standard, rotated , and ), the BB7 copula (standard, rotated , and ), the BB8 copula (standard, rotated , and ), the Tawn type 1 copula (standard, rotated , and ) and the Tawn type 2 copulas (standard, rotated , and ). The estimated bivariate copulas with their corresponding parameters are displayed in Appendix A for completeness.

After the r-vine copula structure, copula families and relevant parameters were estimated, the tail dependence coefficients (TDC’s) are estimated using the simulation procedure provided by Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia (2019). In each of the simulations, samples are drawn of the 15 indices and the TDC’s are calculated. The lower and upper thresholds for the TDC’s expressed in equations (11) and (12) are and , respectfully.

The values displayed in Table 4 are the mean values of the TDC’s and the significance levels are determined using the confidence intervals created by the simulations. The top right panel of Table 4 shows the upper TDC’s, whereas the lower TDC’s are considered in the bottom left panel. To discern between contagion and interdependence, one considers the upper and lower TDC simultaneously. If one observes that both the upper and lower TDC are significantly different from zero, then interdependence is observed since 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, one can state that contagion is observed since significant co-movement of variances is only observed during extreme variances.

Table 4[[2]](#footnote-2): Tail dependence coefficients for the 15 indices.

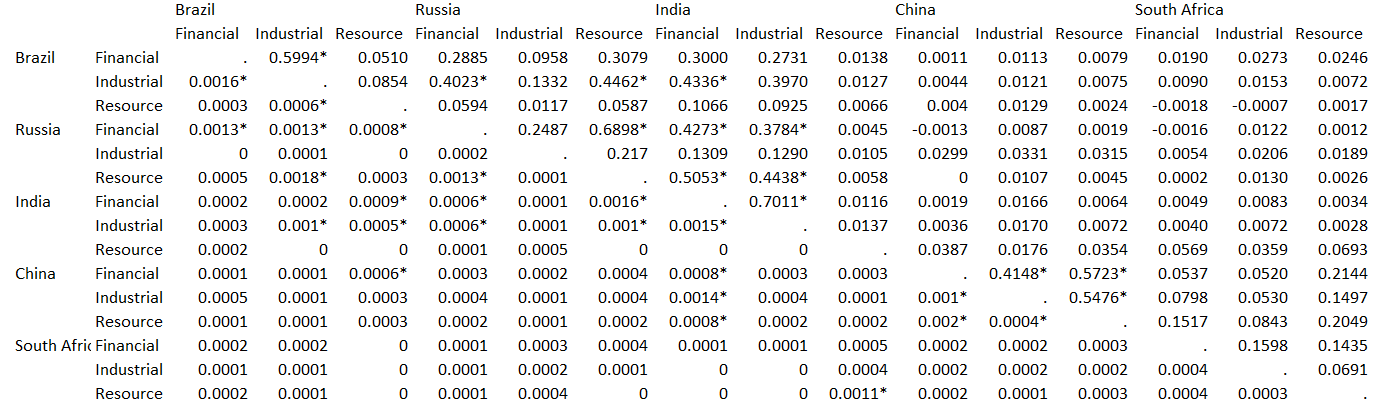


Table 4 shows that only a select few sectors display contagion or interdependence. Most notably, South Africa displays no relationships with any of the other countries in the BRICS grouping. This is in line with numerous studies that question the validity of including South Africa within the BRICS grouping (see, for e.g. Smith (2013), Davies (2013) and Anuoluwapo, Abdul-Wasi, & Edwin (2018)). These and other studies argue that South Africa may not belong within the BRICS grouping since it does not share the same characteristics as the other countries do, like large populations or rapid economic growth. One should note however that the tail dependence coefficients used in this study are symmetrical measures (Joe, 1997). Thus, if a relationship is only unidirectional, the TDC’s may fail to identify it. This may explain why the TDC’s indicate no relationship, whilst other authors have identified that South Africa can be effected by the other countries within the BRICS grouping, whilst not influencing the other countries (Bonga-Bonga, 2018).

Country specific network diagrams are used in figure (2) – (5) to visually display the results shown in Table 4. Solid lines indicate cases where interdependence is observed. Dashed lines correspond with cases where contagion is observed. The indices *F, I and R* represent the Finance, Industrial and Resources sector of a country, respectively.

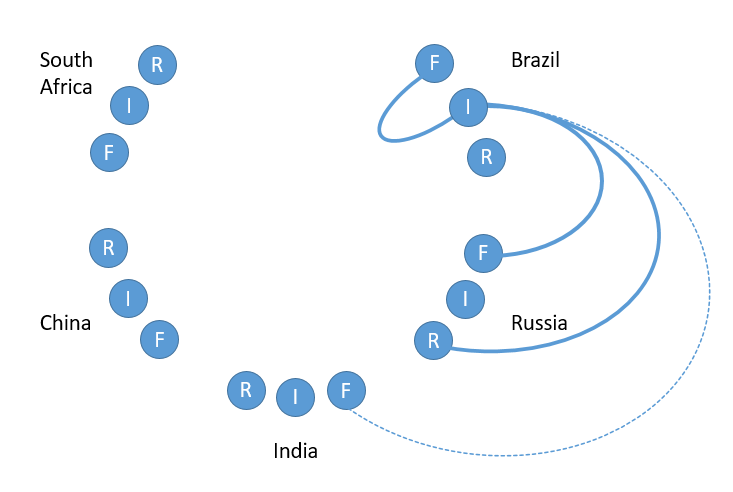


Figure 2: Network diagram of Brazil

Figure 2 displays all the interdependence and contagion events associated with Brazil. Interdependence is observed between Brazil’s Financial and Industrial sectors. Also, Brazil’s Industrial sector is the only sector that experiences contagion or interdependence with sectors outside of Brazil. The Industrial sector experiences interdependence with the Financial and Resource sectors of Russia. Also, it experiences contagion with the Financial sector of India. Furthermore, no contagion or interdependence is observed between Brazil and China. This implies that extreme shocks in China’s economy does not impact Brazil significantly. This is interesting since China is one of Brazil’s biggest trading partners in terms of imports and exports. One should also note that the Resource sector of Brazil shows shares no contagion or interdependence with other sectors. This might be explained by the fact that Brazil is known for their exports of Resources. 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 like iron ore and crude oil, most of these items are mostly insensitive to extreme market movements.

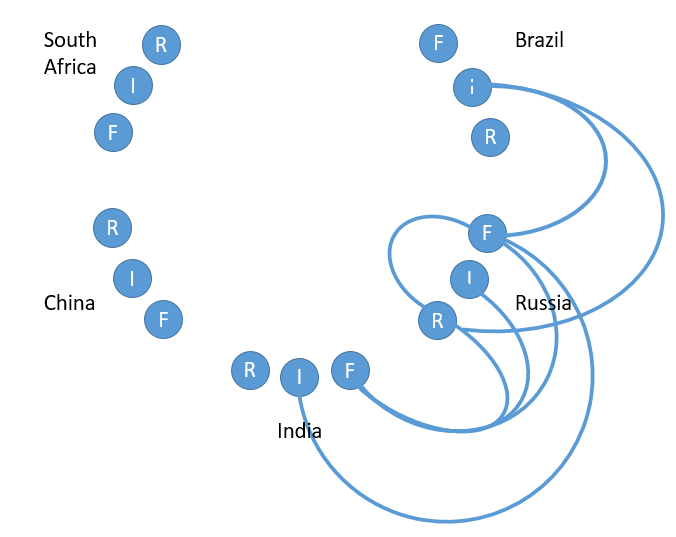


Figure 3: Network diagram of Russia

Figure 3 displays 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 considerable numbers 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 spillover 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 Finance sector of India. Adding on 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 been growing since the Cold War (Bhaskar, 2019). In addition, continuous efforts have been initiated to further strengthen their ties. In example of this is their commitment to increase bilateral trade to US$30 billion in 2025, up from US$9.4 billion in 2017 (Embassy of India Moscow, 2014).

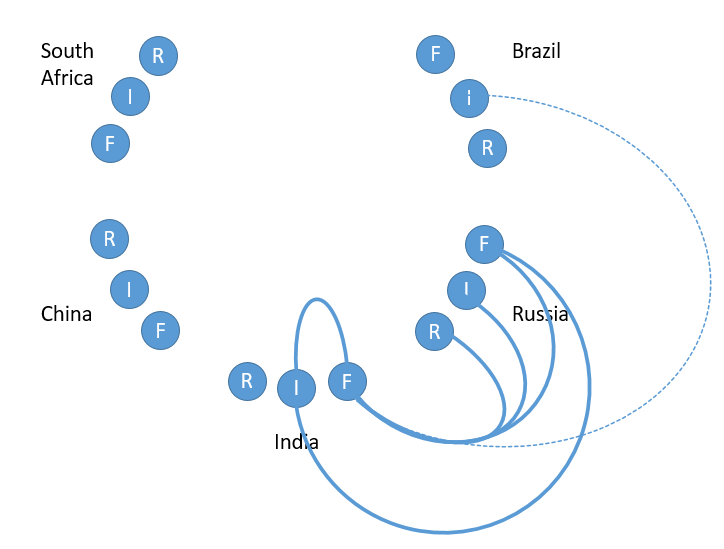


Figure 4: Network diagram of India

Figure 4 displays all the interdependence and contagion events associated with India. Interdependence is observed between India’s Financial and Industrial sectors. Most of the relationships are concentrated with the sectors of Brazil and Russia. As stated before, this may be caused by the continuous efforts of India and Russia to strengthen their bilateral relationships. Adding to this, India’s main import category is raw mineral products like crude oil (18%) and coal briquettes (4.7%) and these are some of the main exports of Brazil and Russia.

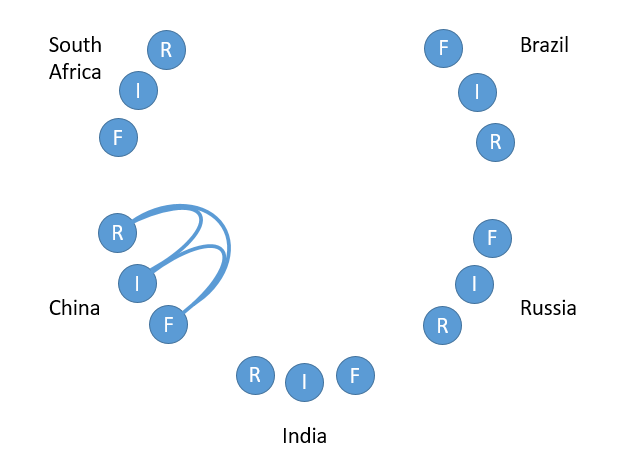


Figure 5: Network diagram of China

Figure 5 displays all the interdependence and contagion events associated with China. China’s economy seems to be the most integrated since all of its sectors experience 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. This may be explained by the fact that the tail dependence coefficients can fail to detect contagion or interdependence if the relationship is unidirectional (Joe, 1997).

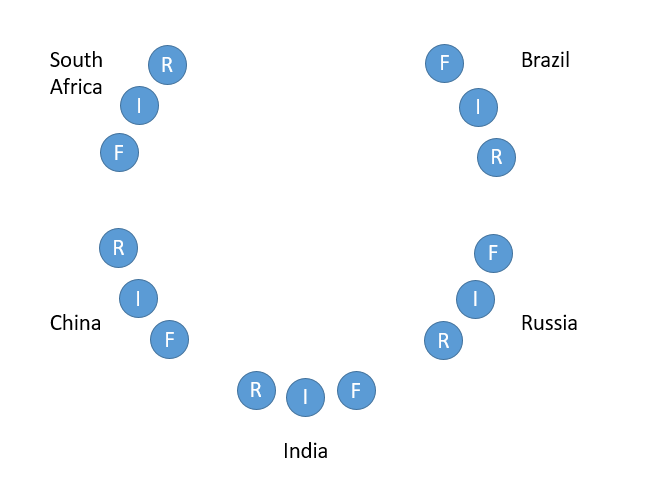


Figure 6: Network diagram of South Africa

Figure 6 displays 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 the findings of others who question the inclusion of South Africa within the BRICS grouping.

The results from Figures (2) – (6) show that in most cases, interdependence is observed opposed to contagion. Interdependence between sectors of different countries can be explained by continuous efforts to align economic policies. The most notable example of this is between Russia and Brazil. Interdependence within country on the other hand is 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. Also, 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 Financial sectors of the BRIC countries play a critical role in the growth of other sectors within country. Similar findings are noted by Ariq (2016) and Mugova (2017) who found 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 one invests in the Financial Sector together with another sector in the same country.

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

# **Chapter 5 Conclusion**

This study aimed at providing a new approach to distinguish between contagion and interdependence by using an R-vine Copula approach coupled with analysing tail dependence coefficients. Contrary to other studies that only focus on identifying contagion (Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia, 2019), this study was able to distinguish between contagion and interdependence. To discuss the contribution to this line of literature, a study is conducted on the contagion and interdependence of the Financial, Industrial and Resource sectors of all the BRICS countries, i.e. the sectors of Brazil, Russia, India, China and South Africa.

In most cases where strong co-movement was observed, one could find that interdependence instead of contagion is observed. This means that where co-movement existed, we could not find evidence of contagion but rather of interdependence. The most notable case is the interdependence of the sectors of Russia and India. From an investors perspective, it suggests that one should invest with caution if one is to invest in Russia as well as India. This is due to normal portfolio optimization techniques relying heavily on traditional correlation estimates that may fail to detect the relationships between assets that the suggested technique can identify. 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 also observed by others like Ariq (2016) and Mugova (2017). The latter studies identified that growth in the financial sector leads to growth in other sectors within the BRICS context. From a portfolio optimization perspective, it suggests that investing in the Financial sector and another sector within the same BRICS country may leave a portfolio over exposed.

The question as to whether South Africa should be in the BRICS grouping is also addressed in this study. As in Smith (2013), Davies (2013) and Anuoluwapo, Abdul-Wasi, & Edwin (2018), it is found that caution should be used if one considers identifying South Africa as being similar to its cohorts in the BRICS grouping. This is due to the fact that no significant relationships with South Africa could be identified.

Overall, the results of this study will help asset and portfolio managers alike to better analyse the relationships and transmission of shocks between the BRICS countries. The results are also similar to Ahmad, Mishra and Daly (2018) who found that the BRICS nations can be considered a heterogeneous asset class if careful consideration is taken whilst investing. Moreover, practitioners will be able to discern between contagion - significant correlation during turmoil market regimes - and interdependence – significant correlation during tranquil and turmoil market regimes – using the proposed technique.

(Longin & Solnik, 2001) (Markowitz, 1952) (Elton, Gruber, & Padberg, 1976) (Ledoit & Wolf, 2004) (Ang & Bekaert, 2002) (Campbell, Koedijk, & Kofman, Increased Correlation in Bear Markets, 2002) (Graflund & Nilsson, 2002) (Pelletier, 2006) (Forbes & Rigobon, 2002) (Boyer, Gibson, & Loretan, 1999) (Loretan & English, 2000) (Corsetti, Pericoli, & Sbracia, 2005) (Horen, Jager, & Klaassen, 2006) (Billio, Duca, & Pelizzon, 2005) (Ye, Luo, & Liu, Time-varying quantile association regression model with applications to financial contagion and VaR, 2017) (Bonga-Bonga, 2018) (Akhtaruzzaman & Shamsuddin, 2018) (Hu, 2006), (Rodriguez, 2007), (Chollete, Heinen, & Valdesogo, 2009) and (Horta, Mendes, & Vieira, 2010) (Costinot, Roncalli, & Teiletche, 2000), (Chan-Lau, Mathieson, & Yao, 2004) and (Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia, 2019) (King & Wadhwani, 1990) (Lee & Kim, 1993)(Forbes & Rigobon, 2002) (Boyer, Gibson, & Loretan, 1999) (Loretan & English, 2000) (Corsetti, Pericoli, & Sbracia, 2005) (Horen, Jager, & Klaassen, 2006) (Girton & Roper, 1977) (Billio, Duca, & Pelizzon, 2005) (Lyocsa & Horvath, 2018) (Bekhaert, Harvey, & Ng, 2005) (Ye, Zhu, Wu, & Miao, 2016) (Bonga-Bonga, 2018) (Akhtaruzzaman & Shamsuddin, 2018) (Kenourgios & Dimitriou, 2015) (Costinot, Roncalli, & Teiletche, 2000) (Chan-Lau, Mathieson, & Yao, 2004) (Hu, 2006) (Rodriguez, 2007) (Chollete, Heinen, & Valdesogo, 2009) (Horta, Mendes, & Vieira, 2010) (Paul & Gideon, 2017) (Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia, 2019) (Campbell, Koedijk, & Kofman, Increased Correlation in Bear Markets, 2002) (De Lira Salvatierra & Patton, 2015), (Patton, 2006) (Jondeau & Rockinger, 2006) (BanSaida, 2018), (Smith, 2013), (Davies, 2013) and (Anuoluwapo, Abdul-Wasi, & Edwin, 2018).

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# Appendix A

|  |  |  |  |
| --- | --- | --- | --- |
| Indices | Copula Family | Param1 | Param2 |
| B F and B I | Frank Copula | 0.403920025 | 0 |
| B F and B R | Student T Copula (t-copula) | 0.030603436 | 14.47559428 |
| B F and C F | Rotated Bb8 Copula (180 Degrees; “survival Bb8”) | 1.11884267 | 0.932875171 |
| B F and C I | Gaussian Copula | 0.089196284 | 0 |
| B F and C R | Frank Copula | 0.645094952 | 0 |
| B F and I F | Bb1 Copula | 0.080271125 | 1.053000587 |
| B F and I I | Rotated Gumbel Copula (180 Degrees; “survival Gumbel”) | 1.03732215 | 0 |
| B F and I R | Frank Copula | -0.07725637 | 0 |
| B F and R F | Student T Copula (t-copula) | 0.002086074 | 24.61601211 |
| B F and R I | Tawn Type 1 Copula | 1.246222193 | 0.030254288 |
| B F and R R | Frank Copula | 0.199508218 | 0 |
| B F and S F | Frank Copula | 0.202117017 | 0 |
| B F and S I | Rotated Tawn Type 1 Copula (180 Degrees) | 1.235167256 | 0.305559754 |
| B F and S R | Student T Copula (t-copula) | 0.376102886 | 8.286966777 |
| B I and B R | Clayton Copula | 0.044355553 | 0 |
| B I and C F | Rotated Joe Copula (270 Degrees) | -1.011923726 | 0 |
| B I and C I | Clayton Copula | 0.036834099 | 0 |
| B I and C R | Rotated Clayton Copula (180 Degrees; “survival Clayton”) | 0.021582103 | 0 |
| B I and I F | Clayton Copula | 0.025240385 | 0 |
| B I and I I | Rotated Tawn Type 2 Copula (270 Degrees) | -1.676139656 | 0.006214324 |
| B I and I R | Tawn Type 1 Copula | 1.14667525 | 0.019567307 |
| B I and R F | Rotated Tawn Type 2 Copula (180 Degrees) | 1.363159099 | 0.004994213 |
| B I and R I | Student T Copula (t-copula) | -0.026159735 | 21.61340004 |
| B I and R R | Student T Copula (t-copula) | 0.0328779 | 20.60547115 |
| B I and S F | Rotated Tawn Type 2 Copula (180 Degrees) | 1.067597973 | 0.110723167 |
| B I and S I | Student T Copula (t-copula) | 0.039460244 | 15.01529267 |
| B I and S R | Student T Copula (t-copula) | 0.645701136 | 2.854077527 |
| B R and C F | Gaussian Copula | 0.039152401 | 0 |
| B R and C I | Rotated Joe Copula (270 Degrees) | -1.017875021 | 0 |
| B R and C R | Rotated Joe Copula (180 Degrees; “survival Joe”) | 1.007096811 | 0 |
| B R and I F | Rotated Gumbel Copula (180 Degrees; “survival Gumbel”) | 1.015388137 | 0 |
| B R and I I | Rotated Tawn Type 2 Copula (90 Degrees) | -2.729205887 | 0.002036801 |
| B R and I R | Rotated Clayton Copula (90 Degrees) | -0.007363907 | 0 |
| B R and R F | Frank Copula | 0.112707181 | 0 |
| B R and R I | Clayton Copula | 0.041680522 | 0 |
| B R and R R | Student T Copula (t-copula) | 0.008215401 | 16.45959515 |
| B R and S F | Student T Copula (t-copula) | 0.010267215 | 18.16715116 |
| B R and S I | Student T Copula (t-copula) | -0.008259976 | 14.06650985 |
| B R and S R | Student T Copula (t-copula) | -0.053243771 | 5.717344532 |
| C F and C I | Rotated Joe Copula (90 Degrees) | -1.018483618 | 0 |
| Appendix A continued |  |  |  |
| C F and C R | Rotated Clayton Copula (90 Degrees) | -0.028955752 | 0 |
| C F and I F | Rotated Tawn Type 2 Copula (270 Degrees) | -2.61109149 | 0.003901065 |
| C F and I I | Rotated Gumbel Copula (180 Degrees; “survival Gumbel”) | 1.022933218 | 0 |
| C F and I R | Student T Copula (t-copula) | 0.014514778 | 23.69426226 |
| C F and R F | Student T Copula (t-copula) | 0.010238621 | 12.08934695 |
| C F and R I | Rotated Joe Copula (180 Degrees; “survival Joe”) | 1.029362866 | 0 |
| C F and R R | Student T Copula (t-copula) | -0.023189068 | 20.67145807 |
| C F and S F | Bb7 Copula | 1.020254233 | 0.052501965 |
| C F and S I | Student T Copula (t-copula) | 0.093014122 | 23.13967843 |
| C F and S R | Student T Copula (t-copula) | 0.751829137 | 3.440027276 |
| C I and C R | Frank Copula | 0.056518384 | 0 |
| C I and I F | Rotated Tawn Type 1 Copula (90 Degrees) | -8.05343661 | 0.002429346 |
| C I and I I | Rotated Joe Copula (270 Degrees) | -1.022025887 | 0 |
| C I and I R | Rotated Joe Copula (180 Degrees; “survival Joe”) | 1.016380552 | 0 |
| C I and R F | Rotated Clayton Copula (270 Degrees) | -0.006504063 | 0 |
| C I and R I | Student T Copula (t-copula) | 0.055738487 | 6.372028273 |
| C I and R R | Rotated Tawn Type 2 Copula (270 Degrees) | -2.475535154 | 0.007238073 |
| C I and S F | Tawn Type 2 Copula | 1.34089995 | 0.015552624 |
| C I and S I | Frank Copula | 0.978559193 | 0 |
| C I and S R | Rotated Bb7 Copula (180 Degrees; “survival Bb7”) | 1.218176216 | 0.293824006 |
| C R and I F | Student T Copula (t-copula) | -0.007877647 | 19.6655432 |
| C R and I I | Clayton Copula | 0.016407826 | 0 |
| C R and I R | Rotated Gumbel Copula (180 Degrees; “survival Gumbel”) | 1.018302107 | 0 |
| C R and R F | Rotated Gumbel Copula (270 Degrees) | -1.008281415 | 0 |
| C R and R I | Clayton Copula | 0.021887166 | 0 |
| C R and R R | Rotated Tawn Type 2 Copula (180 Degrees) | 1.855424958 | 0.004988647 |
| C R and S F | Student T Copula (t-copula) | 0.05061469 | 9.644426446 |
| C R and S I | Student T Copula (t-copula) | 0.03488207 | 17.55473206 |
| C R and S R | Student T Copula (t-copula) | 0.256311535 | 2.437292831 |
| I F and I I | Tawn Type 2 Copula | 1.183842438 | 0.014341739 |
| I F and I R | Rotated Tawn Type 2 Copula (180 Degrees) | 8.827424789 | 0.0001 |
| I F and R F | Rotated Gumbel Copula (90 Degrees) | -1.006228603 | 0 |
| I F and R I | Rotated Gumbel Copula (180 Degrees; “survival Gumbel”) | 1.050875371 | 0 |
| I F and R R | Student T Copula (t-copula) | 0.040084804 | 6.818085721 |
| I F and S F | Student T Copula (t-copula) | 0.113162789 | 9.46199281 |
| I F and S I | Student T Copula (t-copula) | 0.133018357 | 11.64262989 |
| I F and S R | Student T Copula (t-copula) | 0.629355849 | 2.520445939 |
| I I and I R | Rotated Tawn Type 2 Copula (180 Degrees) | 1.282286544 | 0.013653209 |
| I I and R F | Bb7 Copula | 1.013234882 | 0.037440962 |
| I I and R I | Tawn Type 1 Copula | 1.087640836 | 0.124663101 |
| I I and R R | Rotated Tawn Type 2 Copula (180 Degrees) | 1.162547078 | 0.097068671 |
| I I and S F | Rotated Gumbel Copula (180 Degrees; “survival Gumbel”) | 1.026229334 | 0 |
| I I and S I | Student T Copula (t-copula) | 0.166189097 | 5.282905213 |
| I I and S R | Student T Copula (t-copula) | 0.308628466 | 5.616249778 |
| I R and R F | Frank Copula | 0.427204119 | 0 |
| I R and R I | Frank Copula | 0.333206727 | 0 |
| I R and R R | Gaussian Copula | 0.07597931 | 0 |
| I R and S F | Gaussian Copula | 0.069935135 | 0 |
| I R and S I | Student T Copula (t-copula) | 0.109032685 | 30 |
| I R and S R | Student T Copula (t-copula) | 0.268114297 | 6.147600194 |
| R F and R I | Frank Copula | 0.30653249 | 0 |
| R F and R R | Rotated Gumbel Copula (180 Degrees; “survival Gumbel”) | 1.023122846 | 0 |
| R F and S F | Rotated Tawn Type 2 Copula (180 Degrees) | 1.139386431 | 0.209515627 |
| R F and S I | Frank Copula | 0.699789335 | 0 |
| R F and S R | Student T Copula (t-copula) | 0.330077652 | 6.978830796 |
| R I and R R | Student T Copula (t-copula) | 0.036117273 | 14.33584958 |
| R I and S F | Tawn Type 2 Copula | 1.085166713 | 0.237980917 |
| R I and S I | Student T Copula (t-copula) | 0.085546055 | 14.81416199 |
| R I and S R | Student T Copula (t-copula) | 0.13424499 | 9.150443647 |
| R R and S F | Frank Copula | 0.596633966 | 0 |
| R R and S I | Student T Copula (t-copula) | 0.102220225 | 15.67180519 |
| R R and S R | Student T Copula (t-copula) | 0.470385299 | 2.113051916 |
| S F and S I | Gumbel Copula | 1.024622742 | 0 |
| S F and S R | Student T Copula (t-copula) | 0.224322574 | 9.408960547 |
| S I and S R | Rotated Bb7 Copula (180 Degrees; “survival Bb7”) | 1.21153283 | 0.284703839 |
|  |  |  |  |

1. 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 [↑](#footnote-ref-1)
2. 1% level of significance indicated with an asterisk. [↑](#footnote-ref-2)