BRICS sectoral contagion using R-vine copulas

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Abstract

This study considers contagion effects among the sectors of the BRICS (Brazil, Russia, India, China and South Africa) economies by considering a regular vine copula approach and inspecting the tail dependence coefficients. Most upper tail dependence coefficients are observed to be insignificant, indicating no contagion when the sectoral indices are appreciating. The lower tail dependence coefficients are significant in the majority of the cases, indicating contagion between some of the sectors in the BRICS economy when the indices are depreciating. Most notably are the contagion effects observed between South Africa, Russia and Brazil and the other BRICS nations. Also, it is found that China only exhibits contagion with South Africa.

Keywords: Regular Vine Copula, Tail Dependence Coefficients, BRICS

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# Introduction

From the development of the minimum variance portfolio (Markowitz, 1952), investors have become ever more creative in the methods used to diversify their portfolios. Although continuous international market maturity and integration has provided investors with a plethora of additional opportunities for diversification, it has also allowed the prices of commodities to be more integrated and added additional risks that can be difficult to measure.

With markets that continue to integrate, it is natural that the co-movement of prices be observed (Forbes & Rigobon, 2002). Whilst some of the co-movement of prices can be explained by traditional economic theory and measured by simple correlation estimates, there are times where the relationships between prices need additional care in the estimation procedure. For example, it has been observed that correlation structures can change directly after a shock in the market (King & Wadhwani, 1990), which can limit the benefits of portfolio diversification over that time. In general, this is referred to as contagion.

contagion has been observed and measured by a variety of authors during financial crises like the US stock market crash of October 1987 (Lee & Kim, 1993), the Mexican peso breakdown of 1994 (Rodriguez, 2007), the East Asian crisis of 1997 (Horen, Jager, & Klaassen, 2006) and the US market crash of 2007-2009 (Kenourgios & Dimitriou, 2015). Finding the exact definition of contagion has however been a matter of debate, with most of the empirical work either following one of two definitions. The first definition states that contagion is defined as the significant surge of correlation between two markets after a shock in one of the markets occurred (Forbes & Rigobon, 2002). The second defines contagion as the excess correlation between two markets that cannot be explained by economic fundamentals (Bekhaert, Harvey, & Ng, 2005). The former definition however appeals to most authors since it provides the opportunity of testing whether inter-market linkages are temporal or permanent in fashion following a negative shock.

These negative shocks can cause unexpected spill overs which can dramatically affect the expected risk and profitability of financial assets (Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia, 2019). Thus, measuring contagion is becoming ever more relevant since international investors need more reliable estimates used in portfolio optimization and hedging, especially in times of economic turmoil where portfolio diversification is most relevant.

Investing in emerging markets have been observed to be an effective tool for international diversification since developed markets tend to have lower costs of capital whilst emerging markets provide a higher return on capital (Henry, 2007). A natural group of countries that are considered for investment are the BRICS countries, i.e. Brazil, Russia, India, China and South Africa, since it consists of 5 major emerging economies that provide 23.2% of the world GDP as of April 2018 (IMF, 2018). Since the idea of diversification is to limit the effects of negative shocks on one’s portfolio, this practice leads to two natural questions in the context of contagion. The first is the extent of contagion between international markets and the BRICS countries. This line of literature has been observed from authors like Zhang, Li and Yu (2013), Bekiros (2014), Jin and An (2016), Mensi, Hammoudeh, Nguyen et al (2016), Paul and Gideon (2017) and Ji, Bouri and Roubaud (2018). The second question is the extent of contagion between the BRICS countries themselves. This has been done by Bonga-Bonga (2018) who studied the contagion effects from South Africa to the other BRICS countries. This line of literature is extended by Ahmad, Mishra and Daly (2018) who study sectorial contagion within BRIC (without South Africa) and between BRIC and global markets using directional spill over and conditional correlation models. Although the latter authors provide us with a method to measure contagion on a sectorial level, the methodology that is used only allows for linear relationships and they fail to include South Africa in their study. This study aims to build on this line of literature by considering the possible non-linear contagion effects between sectorial indices as well.

This paper focusses on identifying contagion through the Financial, Retail and Industrial sectors of BRICS by utilizing a regular vine copula approach. This provides two important contributions towards the literature. Firstly, the regular vine copula approach considers non-linear relationships that can forge contagion, instead of only considering linear relationships. Secondly, this approach provides us with a wide array of possible correlation structures, instead of a correlation structure that is assumed to be fixed. Both contributions are important since the form of the relationship or correlation structures between indices cannot be assumed beforehand. Lastly, this paper contributes to the line of research that considers country-to-country (within sector) contagion, sector-to-sector (within country) contagion and across country and sector contagion.

# 2. Literature Review

There has been a wide array of authors that have developed models to consider contagion. The initial studies of contagion focussed mainly on testing whether correlations between equity markets changed 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. 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 shock. This leads to the finding that heteroscedasticity in market indices will naturally lead to higher correlations during a financial crisis. 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 simply co-movement 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.

Multiple regression techniques have been considered to study contagion whilst circumventing the issues arising from correlation analysis. This methodology of analysing contagion was introduced by (Horen, Jager, & Klaassen, 2006) who considered the 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. In line with this methodology, (Billio, Duca, & Pelizzon, 2005) incorporate regime switching models in detecting contagion. By using Markov switching Error Correction Models, the authors provide a way to ensure that the crisis periods are endogenously defined. 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. To test their methodology, the authors tested for contagion between the European stock market, Hong Kong stock market and the American Stock market during the Asian crisis of 1997. By utilizing time-varying quantile regression, (Ye, Luo, & Liu, 2017) studied contagion between the Asian, US, and European equity markets during the 2007-2009 banking crisis. The authors make use of the quantile-specific odds ratio (qor) that indicates the odds of two random variables simultaneously being below their 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. 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) by using a two-factor model to study contagion between three regions, namely Europe, Latin America and Southeast Asia. The factors that are used are a regional equity portfolio return and U.S. equity market return. This is expanded by modelling return with a Generalised Auto Regressive Conditional Heteroscedasticity (GARCH) model with asymmetry. 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 the 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 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 contagion between equity markets has received much attention in recent literature through the inaugural study by (Costinot, Roncalli, & Teiletche, 2000). The authors use Normal and Extreme Value copulas to study 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 and bear and bull market contagion. 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. 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 study 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 the definition of contagion episodes and extreme events become endogenous to the model. In studying multivariate dependence structures, (Chollete, Heinen, & Valdesogo, 2009) in turn does 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 limit 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 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. Contagion from 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 paper utilizes 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. Contrary to the latter paper, this article extends on this line of literature by considering contagion on a sectoral level for the BRICS countries. The importance of this study stems from the fact that diversification strategies by modern investors can underestimate the correlation between different sectoral indices, hence introducing additional risk into their portfolios.

# 3. Methodology

this paper makes use of the regular Vine-Copulas approach to study contagion between the different 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. Since the copula approach allows one to first model the marginals which, in turn, is used to filter the data, the first two moments of each series are modelled with an model with student t innovation distribution.

## 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. 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. To identify the model specification of each series, a range of models are estimated on 75% of the data, where after the out of sample Mean Squared Error (MSE) is determined on the remaining 25%. The model specification with the lowest MSE is used as the final model (Tsay, 2010). After the final model is estimated, the residuals are determined which are then transformed to using the Probability Integral Transform (PIT).

## 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 paper 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.

## 3.3 Tail Dependence Coefficients (TDC)

To provide an estimate of the upper and lower tail dependence between the variables, the tail dependence coefficients in terms of copulas developed by Joe (1997) is considered:

(9)

(10)

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.

# 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 returns 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.

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, indicating a high level of risk 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 at and India’s Industrial and Financial sectors with a correlation coefficient at . 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 at . Although these results do not seem promising, one needs to note the serious limitations of unconditional Pearson correlation coefficients in this setting (Cubillos-Rocha, Gomez-Gonzalez, & Melo-Velandia, 2019). These correlations do not provide us with any indication as to whether correlations are different in normal or turbulent times. They are also only 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.

Table 3: Marginal model specification



The first step in the copula methodology is to find the appropriate marginal models for the different indices. Using the procedure described by Tsay (2008), the best marginal models are chosen by using the specification that minimises the out of sample MSE. The results of the models for each series are reported in Table 3. All the chosen models have some variation of the parameters, but it is interesting to note that Russia’s Financial sector consists of no mean equation.

Using the residuals of the specified models, the regular vine structure is estimated using the procedure described by Dißmann, Brechmann, & C. Czado (2013). The appropriate tree structure is found by maximizing the sum of the absolute Kendall taus. 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 that are considered 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. Most of the upper TDC’s are insignificant, indicating that contagion effects are not present during periods of index appreciation. The cases where this is observed are all within country and relates to the Financial sector of a country. These are between Brazil’s Financial and Industrial sectors, Russia’s Financial and Resource sectors, India’s Financial and Industrial sectors and South Africa’s Financial and Industrial sectors. These results indicate that the Financial sectors of these 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.

Table 4[[1]](#footnote-1): Tail dependence coefficients for the 15 indices.



In contrast with the upper TDC’s, a considerable amount of the lower TDC’s are significant at a 1% or 5% level, indicating that some of the sectors within BRICS experience contagion effects during periods of extreme index depreciation.

All the countries experience within country sector-to-sector contagion during crisis periods.

Brazil’s Financial and Industrial sector shows strong signs of contagion with all other indices except with the Chinese sector indices. It’s Resource sector index however only shows contagion effects with Russia’s Resource sector and India’s Financial sector.

All of Russia’s sectors show a remarkedly similar pattern. Most of the indices experience significant contagion effects with the other sectoral indices in the study, except with the sectoral indices of China.

India’s sectoral indices also have a high level of contagion with the other sectors except for the sectors of China. One clear distinction here is India’s Industrial sector that has no contagion effects with the sectors of South Africa.

China provides us with very interesting results. Here we do not observe any contagion effects with the other BRICS nations except with South Africa. Within sector and cross sector contagion is observed between the Financial and Industrial sectors of South Africa and China. Within sector contagion is also observed between the Resource sector of the two countries.

South Africa’s sectoral indices display contagion with most other sectoral indices within the BRICS countries. The strongest contagion effects are observed with Russia. All South Africa’s sectors except South Africa’s Financial and Russia’s Industrial sectors experience contagion.

The overall results from Table 4 indicate that contagion does occur within the sectors of the BRICS economy but not in an overall setting. China seems to be decoupled from the contagion effects of the different countries. The only notable contagion effects involving China is observed with South Africa. Contagion is also observed between the sectors of India and mostly Brazil and Russia, but not so much with China and South Africa. The results in this paper suggest that in some cases BRICS can be considered as a heterogeneous asset class but that care needs to be taken in the selection of what assets to include to ensure a well-diversified portfolio. The results in this paper 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 and India provide additional opportunities for diversification when compared to the sectors of Brazil and Russia.

# 5. Conclusion

This paper assesses the levels of contagion between the Financial, Resource and Industrial sectors of the BRICS (Brazil, Russia, India, China and South Africa) countries using a regular vine copula model. Contagion is measured by considering the significance of the tail dependence coefficients (TDC’s).

Upper TDC’s were found to be insignificant in most cases. The only cases where it was observed to be significant are between sectors that are within the same country. This result indicates that cross country contagion is not observed during times of large index appreciation. The opposite is observed when the lower TDC’s are considered. In most cases the lower TDC’s were significant at a 1% or 5% level, indicating that within country and cross country contagion is observed during periods of large index depreciation, i.e. when the markets are in distress. This implies that the advantages of diversification are greatly reduced within some of the BRICS sectors and care needs to be taken when these indices are used for this purpose.

The study shows that the sectoral indices of China experience the smallest amount of contagion. After China, India experiences the lowest contagion levels. These results are in line with studies such as Ahmad, Mishra and Daly (2018) who indicate that these two countries can be used in portfolio allocation.

The findings of this paper should be of interest for investors and portfolio managers if they are considering using BRICS as a method for portfolio diversification.

(Joe, 1997)(Sklar, 1959)(Bedford & Cooke, Vines - a new graphical model for dependent random variables, 2002)(Bedford & Cooke, Probability Density Decomposition for Conditionally Dependent Random Variables Modeled by Vines, 2001)(Deheuvels, 1980)(Mugova, 2017)(Ariq, 2016)

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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 significance levels that were considered are 10%, 5% and 1% and are indicated by one, two or three asterisks, respectively. [↑](#footnote-ref-1)