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Dependence Structure Between Stock Markets of BRICS Countries and Developed Countries: Evidence Using Wavelet and VMD Copula Approaches

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Abstract: This paper investigates the comovement in the stock prices of three developed countries (USA, UK and Japan) and BRICS (developing) countries (Brazil, Russia, India, China and South Africa) using Wavelet Coherence and Variational Mode Decomposition (VMD) based copula approach for the period 2002-2018. We find that not all BRICS states co-move with developed countries, but comovement is led by developed markets. Brazil moves with the USA, both in long-run and short-run. Whearas, China has least interdependence with either of the developed countries, both in long-run and short-run. It is also found that Global Financial Crisis increased the interdependencies between developed and BRICS countries. The results of both the approaches are consistent with each other. We also find that BRICS markets collectively don't act as a group. These findings are essential for investors to make the optimal portfolios or policymakers to make macroeconomic policies.

JEL classifications: G1, F3
Keywords: Copula, Wavelet analysis, Dependence.

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1. Introduction

The developing countries, especially BRICS countries' economies are increasingly receiving more and more interest in research literature due to their amplified share in international trade, excessive returns and fast economic growth. BRICS currently account for more than a quarter of the world's land, 42% of the world's population and 25% of the total world GDP. It is estimated that the stock markets of the BRIC countries account for 41% of the global stock market capitalization (Liu, Hammoudeh, & Thompson, 2013). These countries work closely strategically in an alliance. These countries also hold an annual summit to discuss the possible economic cooperation with each other.

BRICS economies' desire to develop as a source of diversification for developed countires investors created opportunities along with challenges for the developed economies. BRICS markets have had low correlations with the developed markets and because of the relatively isolated nature of markets neglected by the mainstream investors, these markets have produced high levels of returns. For the reasons mentioned above developed countries invested heavily in these developing economies. During 2003-2008, the inflow of outside investment in these countries increased from 77 Billion to 281 billion dollars (UNCTAD 2013). Since these countries present a diversification opportunity for global portfolio investors the investment in these countries in international portfolios is growing in significance. Massive investment from the developed economies has made BRICS economies more liquid, credible, visible and transparent.

However, massive investments by the developed countries also increased the emerging economy's dependence on the developed economies. An adverse event in the developed economies can shake the BRICS countries' markets. For example, after the 2007-2008 global financial crisis (GFC), developing emerging countries like BRICS reencountered quickly to the declining situation in the U.S. financial system and performed poorly (IMF, 2012). Since the 2007-09 it has been seen that the risk spreads across the markets due to market integration. The high risk-return tradeoff has made diversification in traditional assets questionable. Higher levels of integration of global markets have facilitated capital mobility as well as they have increased the volatility spillover between the markets as seen through the GFC of 2007-09. Because, the BRICS countries' share in global markets is increasing, it has therefore started a debate in academic literature, whether these countries are also susceptible to the spillover of global shocks owing to their greater and growing integration. This debate is critical to the policy makers of international diversification for purchasing assets from these markets to build their global portfolios that defy the spillover of the shocks at international level.

Thus, emerging countries stock markets', i.e. BRICS countries, relationship with those of advanced countries is of particular interest for portfolio formation. One purpose of combining BRICS countries into one research is to see how these countries behave together as a group. Majority of the previous literature about contagion emphasis largely on developed markets and emerging markets are neglected by the researchers. Due to the earlier discussed attributes of emerging markets, more research on such markets has been conducted with an emphasis on the time-varying cross-market correlations, particularly during the crisis period. The purpose of the studies on this group is to explore the co-movements level in the global markets and asses to what degree can the shocks to the global financial system can spillover across countries just as GFC 2007-2009 which started from the USA and quickly expanded to the other countries and its trading partners.

There is little research done on the linkages and spillover between the UK and BRICS (Liu et al, 2019; Mensi, Hammoudeh & Kang (2017); Kocaarslan, et al., (2017); Yarovaya& Lau (2016)). The main reasons are following. First, the bulk of studies have been carried on the USA as the country thought to be sole spreader of volatility shocks across the world markets (e.g., Xu &Hamori, 2012), while diversification opportunities for UK and Japan shareholders in the global portfolio are left unstudied. To the best of our knowledge, there are few research studies that investigate the stock market inter-linkages among the USA, UK, Japan and BRICS economies. Therefore, it is vital to bridge this difference to boost understanding of probable international portfolio diversification benefits accessible for USA, UK and Japan investors in developing markets.

Since the early study of Bekaert and Harvey (1995), it has been established that financial markets correlations vary over time. According to Rua and Nunes (2009) the variation of stock return comovement differs throughout time and space. Jong and de Roon (2005) show that the dynamic nature of the integration of stock returns is more pronounced for the developing countries that recently started globalization of their financial markets. Since the stock market is composed of a heterogeneous group of investors, some have short investment horizons others have a long investment horizon. Thus, the time dependence of comovement is essential for market participants. Short-term oriented investors composed of active investors are more concerned about short-term relationships between the markets as given by short term comovements while the longer-term oriented investors are more concerned about the long-term performance of their portfolios. Thus, different investors belonging to different categories across different countries are interested in different types of risk characteristics in their investments.

Since investors are looking for differing correlations in the short and long term, investigation of this issue must be able to separate correlations in the short term and long term. Recent studies investigating the short-term and long-term correlations have used wavelet coherence analysis (Rua and Nunes (2009)). Our use of wavelet coherence technique and VMD (Variational Mode Decomposition) based copula allow us to separate correlations in short and the long-term. Our results reveal that not all BRICS markets have the same correlation with the developed markets. For the portfolio formation purposes, the Chinese market has least correlation with either of the developed countries' markets, both in short and long term and therefore presents the opportunity for diversification. Brazilian market's correlation with the USA is most amongst all the developing-BRICS pairs. Overall the level of correlation between the countries is low, which means BRICS markets are not integrated a lot with the developed countries' markets.

The lead-lag association in Wavelet Coherence Analysis shows that developing countries' markets generally lead BRICS markets. The VMD based copula analysis reveals that BRICS countries markets are more correlated with those of the developed countries in the long run than in the short run. Besides the above mentioned contribution, the study also contribute methodologically by using Wavelet analysis along with VMD based copulas for the developing countries – BRICS data. Our methodology allows us to study the effect of extreme comovements in the short and long run. Not many studies have used a nonlinear measure of dependency for checking extreme dependence between these countries. We use copula functions with VMD decomposition, which makes it easier to identify the extreme dependence in the long and short run. To further

strengthen our results, we prefer a wavelet-based method to DCC-GARCH methodology to study the contagion effect because Wavelet-based approaches provide added evidence on time based interdependence among two different types of markets. The nature of shocks between two markets due to contagion risk is such that the shocks are rapid in terms of spreading and fading in number of days. Therefore, the time base correlation information is very useful to detect such types of shocks (Reboredo and Rivera-Castro, 2013).
This paper makes many contributions to the literature as following. First, there are very few studies that use our proposed methodology for the analysis of the issue of contagion in international financial markets. This is important because of extra advantages/insights obtained from this methodology for studying the correlation between the markets. Second, the UK market is very rarely studied as part of the developed markets, we study the UK market and try to find new insights from the data of the spillover effect between the UK and other BRICS markets. Third, our paper covers the sample period after the global financial crisis, this will help us investigate the long term effect of the GFC on the risk spillover between the countries. Fourth, the results in our paper are important for international management and will help international investors choose their portfolio based on its own risk characteristics.

1. Literature Review

Wei, Liu, Yang, and Chaung (1995) examined contagion from the developed to the emerging markets during 1991-1992 period. USA, Japan and UK were taken as developed economies while Hong Kong and Taiwan were taken as emerging markets. They find the evidence of contagion effect from developed to emerging markets. The findings reveal that Japanese stock market has less impact than the New York market on the Taiwanese and Hong Kong stock markets. Secondly, the Taiwanese stock market is more vulnerable than the Hong Kong stock market to the price and volatility of the developed countries` financial markets.

The empirical research done so far reveals that there is variation in emerging markets in their ability to provide diversification. Some countries are better option for diversification than others in both normal and chaotic periods in the market. Moreover, the results of the studies done to check contagion and volatility spillover are conflicting at the best. One side is of the view that there is strong co-movement between US and China and hence China is not good diversification option Bekiros (2014). On the contrary, Lehkonen and Heimonen (2014) analyzed the relationship in terms of comovement among BRICS and developed markets. Developed markets included UK, Germany, Japan, Canada, Australia and Hong Kong. They find that the diversification option across developed markets have diminished due to the increasing correlation between the countries. Still emerging markets like China present good diversification options. The Chinese market is better investment option than other markets of the BRICS countries. Syriopoulos et al. (2015) also report similar findings where the Chinese stock market is weakly correlated with the US market during the turmoil and crisis than are other BRICS markets.

According to Zhang et al. (2013) the 2007 GFC crisis has altered the correlation structure among the BRICS and developed countries. Russian and Brazil financial markets have stronger correlations with developed countries' markets than Indian and Chinese markets as 70% of BRICS stock markets' conditional correlation series have an increasing long-term relationship with the developed countries' stock markets. Lehkonen & Heimonen (2014) study the asset return co-movement of the Brazil, Russia, India and China) concerning the U.S. for different return periods. They use wavelet analysis to decompose the stock return into various time scales and use the decomposed series as an input for further analysis using the DCC method. Their results show that the level of stock market co-movement depends on the regional aspect. The BRICs have heterogeneous market structure, yet they provide the portfolio diversification benefits. Das et al. (2018) report weaker contagion in Latin American emerging markets as compared to other European and Middle Eastern markets. They also report a permanent change in the correlation structure after the global financial crisis.

Yarovaya & Lau (2016) study the stock market co-movements and diversification benefits available for UK investors having portfolio investments in the BRICS countries equity markets. The results suggest there are diversification advantages of investing in these portfolios for the UK investors. Diversification brings More benefits when investments are made in Chinese stock market. These benefits consist of reduced exposures to shocks to the portfolio. Xu &Hamori (2012) studied the dynamic relationships between the BRIC and New York stock markets throughout 2004 -2010. Their results indicate that the relationship between US and BRIC markets weakened after 2007-09 financial crises. Bianconi et al. (2013) investigate the debt and equity markets of BRICS countries during 2007-09 financial crises. They find that stock markets are hit more than the bond markets during the crisis period. Brazil and Russia are hit more in the financial crisis. Dimitriou et al. (2013) study the contagion effect of the GFC on BRICS countries by using FIAP-ARCH-DCC framework. They find that correlations increase from 2009 onwards. Mensi et al. (2016) study the spillover effect between the US and BRICS countries. They find that there is strong evidence of asymmetry and long memory in the conditional correlations. They also find the standard break date for disruption in the relationships in these markets, which corresponds to bankruptcy Lehman brothers. Mensi et al. (2017) study the spillover effect between developed and BRICS markets. Their results show that there is significant and asymmetric long memory in all of these markets.

Fang et al., (2021) study the risk spillover in financial markets between China and G7 countries. They find that due to greater openness of Chinese economy, Chinese markets are gradually becoming more integrated with international financial markets. They further find that the spillover between Chinese and G7 markets are still largely dominated by the G7 countries. They find that the economic policy uncertainty as the driver of cross border spillover in financial markets. Ji et al., (2020) study the spillover between the US and G7 countries' stock markets using time varying copula models. Their results suggest that the dependence between the US and is time varying. Li, H. (2020) study the risk spillover within the European countries in the context of uncertainty of BREXIT. They find that the relationship of the Britain and with other European countries has weakened.

This paper contributes to this literature in the following ways. Not many studies have used a non linear measure of dependency for checking extreme dependence between developing or emerging countries. Our contribution to the existing literature is as follows. Specifically, to the best of our knowledge, no study has used the combination of wavelet analysis and copula analysis to check the correlation between BRICS and developed countries' markets. This is important. There is only one study (Lehkonen & Heimonen (2014)) which analyzed the connectedness between the developed countries stock markets and the BRICS'. Our paper is different from lehkonen & Heimonen, (2014) as the methodology we adopt allows us to know the lead lag relationship between the two markets under study. This is important as to understand the source of correlation between the two markets by knowing the lead lag causality can help international investors and other policy makers looking after the safety of the markets. Further, we use copula functions with vmd decomposition, which makes it easier to identify the extreme dependence in the long run and in the short run. To the best of our knowledge, our study is the first to investigate the spillover between BRICS and developed markets in the case of extreme shocks to a market in either of the two groups. Extreme shocks to one of the markets reflect the potential crisis situation in that market. The spillover between the markets in case of a crises in one of the markets is very important question, the answer to which may determine the safety of international stock markets. The debate in previous research about whether BRICS constitute a group of countries suitable for diversification as a whole or individually is inconclusive. Therefore, there was a need to conduct a study on this sample which uses a methodology flexible enough to answer the question of dependency in a precise manner. Thus, our paper about risk spillover between advanced economies and BRICS makes two contributions to the literature. First, we measure lead-lag causality in correlations between the advanced-BRICS stock indices pair to measure the contagion between different country indices. Secondly, we use copula functions to measure the tail dependence between the two markets.

2. Methods

In this paper, we use the methodologies of Wavelet Coherence Analysis (WCA) and Variational Mode Decomposition (VMD) based Copulas. By using wavelet analysis, we decompose the time series into time and frequency domain that allow the researchers to differentiate between contagion (short term dependencies) and interdependencies (long run relationship). The co-movement of stock return is known to exhibit tail dependencies. The DCC-GARCH model is able to reveal in the conditional correlations over a specified period of time. We, however, employ a wavelet based approach as they can shed light on the time localized interdependencies and correlations and hence provide additional information. Since we know that shocks to the system of international financial markets are rapid in terms of transmission and decay, therefore a methodology that measures the comovements in terms of time is very useful (Reboredo & Castro,(2013)). Different copulas are used to study different tail dependencies. Variational mode decomposition (VMD) is finally used to decompose the series into short-run and long-run component series. Application of copula models on these decomposed series allows us to measure tail dependence in short and long run.

We firstly check the correlations between the countries using Wavelet Coherence Analysis and then plot the results as the graphs for easy observation. We then use the copula models for checking the tail dependence between the countries. We fit the copula model on the residual of the GJR-GARCH model fitted to the raw return series. We also decompose the data to obtain the long run and short run series.

Wavelet Squared Coherence analysis

There are two methods available to perform the Wavelet analysis: Discrete Wavelet Transform (DWT) or Continuous Wavelet Transform (CWT). Continuous Wavelet Transformation is preferred over DWT because of the ease of interpretation of the results (Shahzad et al., 2017). Wavelet Squared Coherence (WSC) is the ratio of the cross-spectrum to the product of the spectrum of each series and can be regarded as the time localized comovement between the two time-series (Aguiar&Soares, 2011). For details about the methodology, please refer to Grinsted et al. (2004). Wavelet transformation uses wavelet function to transform the time series. The mother wavelet that is used to produce small waves and can be given as:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\,\psi(\frac{t-\tau}{s})$$

The mother wavelet has several properties. It has a mean equal to zero. $\int_{-\infty}^{+\infty} \psi(t)dt = 0.$ Further details can be found in the literature (Grinsted et al., 2004). In our analysis, there are two reasons for using wavelet transform over the Fourier transform. First, while converting time series, Fourier transform exhibits frequency information only while we need for our analysis, both spatial and frequent information which is given by the wavelet transform. The wavelet transformation also has a unique feature of avoiding being infinitely differentiable and allowing smoother interpolation. There are different types of wavelets available for decomposition purposes. We use Morlet wavelets for our purpose of checking the coherence. Fourier transforms of Morlet waves is given by,

$$\psi_\sigma(\omega) = c_\sigma \pi^{-0.25}(e^{\left(-\frac{1}{2}\right)(\sigma-\omega)^2} - k_\sigma e^{\left(-\frac{1}{2}\right)(\omega^2)})$$

Where c_σ is normalization constant and k_σ is the admissibility condition.

The period for Morlet waves is given by the following equation.

$$\psi^M(t) = 1/\pi^{0.25}\, e^{i\omega_0 t} e^{-t^2/2}$$

Where ω_0 is the central wavelet frequency and suggested to be $\omega_0 = 6\,Hz$ (Grinsted et al.,2004;

Rua and Nunes, 2009; Barunikand Vachaand (2016). CWT function W_x is given by.

$$W_x(\tau,s)= \int_{-\infty}^{+\infty} x(t)\psi_{\tau,s}(t)dt$$

The cross wavelet transform of the two series x and y with continuous wavelet transform $W_x(\tau,s)$ and $W_y(\tau,s)$is given by Torrence and Compo (1998) as.

$$W_{xy}(\tau,s) = W_x(\tau,s).W_y(\tau,s)$$

The value of WSC is given by

$$R^2(\tau,s) = \frac{|S\big(s^{-1}W_{xy}(\tau,s)\big)|^2\big)}{S(s^{-1}\big|W_x(\tau,s)|^2)S(s^{-1}\big|W_y(\tau,s)|^2)}$$

The value of R^2 ranges from 0 to 1 and signifies the level of comovement. Where a value of 0 and 1 correspond to a low and high degree of comovements respectively. The lead-lag relationship between the time series is given by the following equation.

$$\theta_{xy} = \tan^{-1}\frac{I(W_t^{xy})}{W_t^{xy}}\theta_{xy}, \in (-\pi,\pi)$$

If the value of θ_{xy} is less than $\frac{\pi}{2}$ then the two series are moving in phase. On the other hand if the value is greater than $\frac{\pi}{2}$ then the series are out of phase.

Variational Mode Decomposition (VMD)

To separate the long run and short-run dynamics of the data, we use variational mode decomposition. In VMD a time series f is decomposed into k modes. Each mode is compressed around a centre pulsation, ω_k which is determined along with decomposition. The decomposition is done by processing the signal in the Fourier domain and reconstruction through Lagrange multiplier. The bandwidth is obtained by solving following minimization problem.

$$\min_{(\mu_k,\omega_k)} = \{\sum_k \left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*\mu_k(t)\right]e^{-j\omega_k^t}\right\|^2\}\ s.t.\sum\mu_k = f$$

Where k is a number of modes, ω, δ and * are respectively frequency, the Dirac distribution, and convolution. Variational modes u and central frequency ω can be obtained through the following Eq.

$$u_n^{n+1} = \left[f - \sum u_i + \frac{\pi}{2}\right]\frac{1}{1+2\alpha+(\omega-\omega_k)^2}$$

$$\omega_n^{n+1} = \frac{\int_0^\infty \omega|\mu_k\omega|^2 d\omega}{\int_0^\infty |\mu_k\omega|^2 d\omega}$$

Copula

Since correlation does not capture tail dependence, the comovement in extreme events, we utilise copula to capture the tail dependence. Copula theory is based on Sklar theorem. Copulas are the functions that describe the relationship between joint probability distribution and the marginal distribution of continuous variables.

$$F_{xy}(x, y) = C(u, v)$$

Where u and v are marginal distribution functions. Our study uses three kinds of copula functions. We use: *t-copula*, which has symmetric tails, *Clayton copula*, which has negative tail dependence and *Gumbel copula*, which has positive tail dependence. T-copula is given by:

$$C(u, v, \rho) = T(t^{-1}(u), t^{-1}(v)) \quad \rho \epsilon [-1,1]$$

Clayton copula is given by:

$$C(u, v, \delta) = \max\{\left(u^{-\delta} + v^{-\delta} - 1\right)^{-\frac{1}{\delta}}, 0\} \qquad \delta \epsilon [-1, \infty)$$

Gumbel copula is given by:

$$C(u, v, \delta) = \max\left((-\log u)^{\delta} + (-\log v)^{\delta}\right)^{\frac{1}{\delta}} \qquad \delta \epsilon [1, \infty)$$

3. Data and hypothesis

We use the daily data for the stock market indices of developed and BRICS countries. The data is publically available from various internet sources. Specifically, we collect the daily returns of *S&P500* (USA), *FTSE100* (UK), *Nikkei 225* (Japan), *IBOVESPA* (Brazil), *RTS* (Russia), *BSE- Sensex* (India), *SSE Composite Index* (China) and Johannesburg Stock Exchange Domestic Company Index (South Africa) from www.finance.yahoo.com. Our sample consists of 4279 daily observations for each index starting from 2002 ending at 2018. Since we want to measure the correlations between developed (US, UK and Japan) and developing markets (BRICS) in a lead lag relationship, we must make arguments about the dymanics of the correlations between the pair of countries. Since, the lead lag relationship between the two markets under study depends on relative development status of the two markets, relative size of the two markets and relative inter-connectedness of the two markets, we expect that correlation between the developed and BRICS markets initiated by the developed countries' markets. Thus, our first hypothesis is as follows.

H_1: *The correlation between the developed markets and BRICS' markets will be led by the developed markets.*

The second hypothesis is related to whether the BRICS countries act as a group with similar characteristics. Given the geographic spread of the BRICS markets around the globe, it would be unrealistic to expect that the BRICS markets act as a group as the correlation between the countries depends on the degree of interaction between them due to factors such as trade between the countries, investment in each others markets and diversification of the markets in terms of their income etc. As a group BRICS countries are not homogeneous in these factors and therefore are expected to have different interaction with different developed markets. Therefore, we state our

H_2: *The BRICS countries do not co-move with developed countries as a group.*

Finally, we expect that correlation between the BRICS-deveoped market pair will be higher in case the two countries are in geographic proximity. Since, the degree of inter connection between the two countries depends on the geographic proximity as the interconnectedness, as through the international trade, is higher in case of geographic proximity. Therefore, we our 3rd hypothesis is as: H_3: *The correlation between the developing-developed country pair will be high for the countries closely located.*

4. Results

We start our analysis from simple correlation matrix of all the indexes in the dataset. Table-1 gives the correlations coefficient between the various pairs of indexes/coutnries. Level of correlation, level of significance and confidence interval for the correlation is given. Overall, there appears to be a range of variation in terms of the level of correlation between variables in our dataset. The correlation between Brazil and US stock markets is highest amongst all the correlation pairs. While the Chinese stock market has the lowest correlation with all the other markets. Overall, the strength of the correlation is moderate to low.

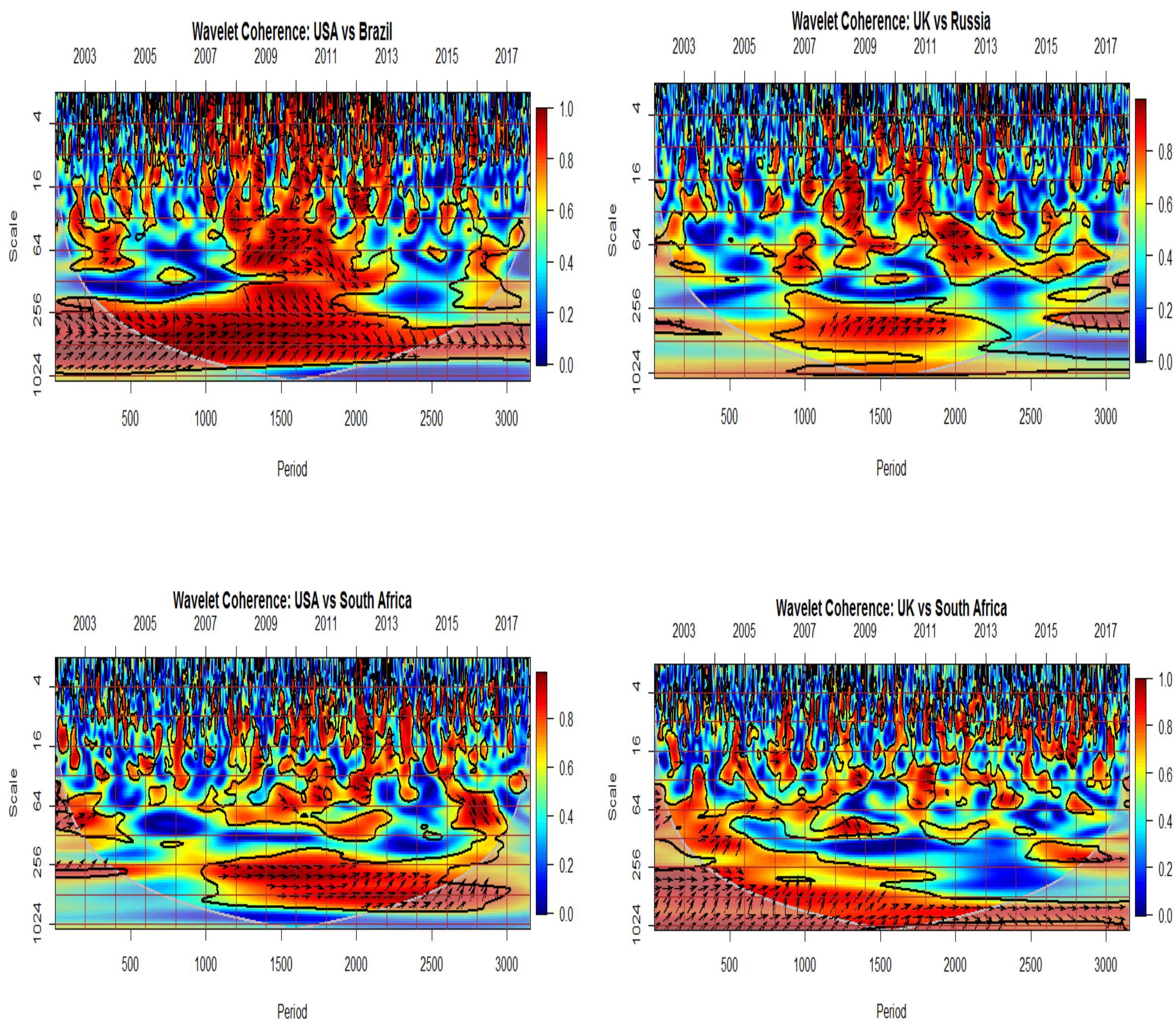
Table 1 ***correlations with confidence intervals***

Variable	India	Brazil	UK	SA	Russia	USA	Japan
1. India							
2. Brazil	.19**						
	[.16, .22]						
3. UK	**-.03**	**.00**					
	[-.06, .01]	**[-.03, .04]**					
4. SA	.25**	.35**	**.30****				
	[.21, .28]	[.32, .38]	**[.07, .14]**				
5. Russia	.03	.04*	**.42****	.07**			
	[-.00, .07]	[.00, .07]	**[.39, .44]**	[.04, .10]			
6. USA	.20**	**.57****	-.02	**.32****	.01		
	[.17, .24]	**[.54, .59]**	[-.06, .01]	**[.29, .35]**	[-.03, .04]		
7. Japan	.14**	.16**	.17**	.27**	.13**	.14**	
	[.10, .17]	[.13, .20]	[.14, .20]	[.24, .31]	[.09, .16]	[.10, .17]	
8. China	.10**	.10**	**.01**	.10**	.04*	**.05****	.13**
	[.07, .14]	[.07, .14]	**[-.02, .05]**	[.07, .13]	[.00, .07]	**[.01, .08]**	[.10, .17]

Note. Values in [ ] indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

To analyze the long term comovement among the markets and the lead-lag relationship, the wavelet analysis is used. The technique used is the wavelet coherence analysis. The frequency here represents days (duration) when the two variables commove at a specific point of time. Since there are 15 pairs (5 BRICS and 3 Developed countries) of data, we have a total of 15 numbers of graphs. It is challenging to present all the graphs here. To keep it simple, we only present graphs of pairs with high correlation and those with low correlation as given by the correlation table (Table-1). Coherence maps for the high and low correlation pairs are given in Figure-1 and Figure-2, respectively.

Figure 1 This figure gives the WSC between the developed and BRICS markets. The four panels represent the highest correlations between the markets as given in Table-1.

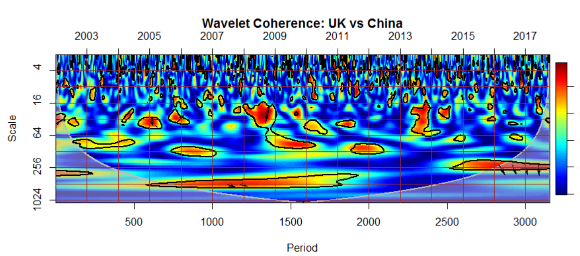


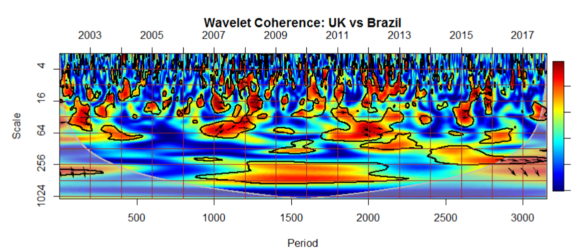
Note: The time period is on the x-axis while frequency is on the y-axis.

Figure 1 presents the graphs for the stock pairs with high correlation, while figure 2 presents graphs for the stock pairs with low correlation. The color bar on the right-hand side of each graph represents the strength of the relationship between the variables in the graphs. Red color represents a strong relationship while the blue color represents the weak relationship between the variables. The heavy black line enclosing the red area shows comovement at 5% level of significance.

The light blue color adjoining the red interface is the edge effect. The direction of the arrows denotes the difference in phase of the market cycle between the two time series. Figure 1 shows the pairs of stock with relatively high correlation as given by the red colour of the graphs and the rightwards pointing arrows. Both the indexes are in phase and pass cyclical effects on each other. USA-Brazil pair shows the highest correlation pair. The arrows are rightwards indicating that the USA market leads the Brazilian market. Correlation is strong both in the long-run and short-run, i.e. both in high frequency and the low-frequency range. In the UK-Russia figure, the red area appears around the global financial crisis, and we see that the UK market leads the Russian market. For the graphs of USA and UK with South Africa, we see that the USA and UK markets lead the South African market. On the scale dimension US-Brazil pair shows strong correlation on both large and small scale (in terms of number of days) during the GFC period. For the rest of the pairs the correlation is higher on large frequency scale than on short scale. Means stocks are correlated in long term than in the short term.

In figure 2, we present the graphs of pairs of markets with low correlation as evidenced by the lighter shade of the graph. We see that Chinese market shows the least correlation with the other markets. The correlation between UK-Brazil and UK-India is also low. The graph for USA-China shows that there is a red area around 2006 to the end of the global financial crisis. The direction of the arrows indicates that the Chinese market is the leading index in this relationship. One thing noticeable from figure-1 and figure-2 is that the correlation between the pairs is mostly in the long run than the short run. In figure-2 this is clear from the lack of red areas on the short scale than in the long scale. We get the same results later as well, with the help of correlation graphs of copula functions. The overall dominance in the lead-lag relationship by the advanced countries shows the evidence in favor of our first hypothesis H1.





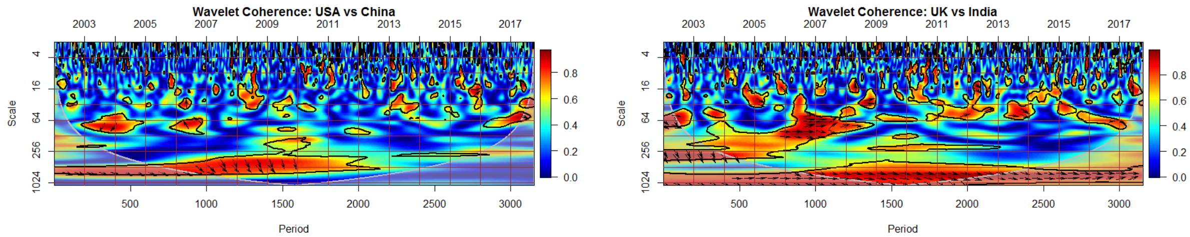


Figure 2 WSC between the pair of developed and BRICS stock markets each. The four panels represent the four pairs of BRICS-Developed markets having low correlation. The horizontal axis denotes the time period, while the vertical axis denotes the frequency.

Table-2 The implication of arrow direction on the wavelet coherence map.

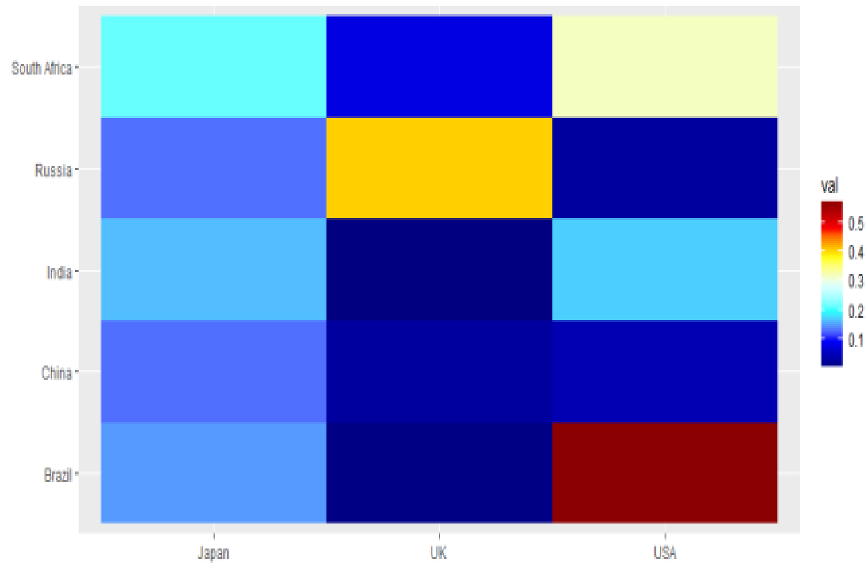
Direction	Implication
→	The first index cyclical phase is in phase with the second index
←	The first index is not in phase with the second index
↗ & ↙	The first index leads the second index
↘ & ↖	The first index lags and follows the lead of the second index

Note: The arrow direction above roughly estimates whether the first variable's cyclical effect influences the other variable or vice versa.

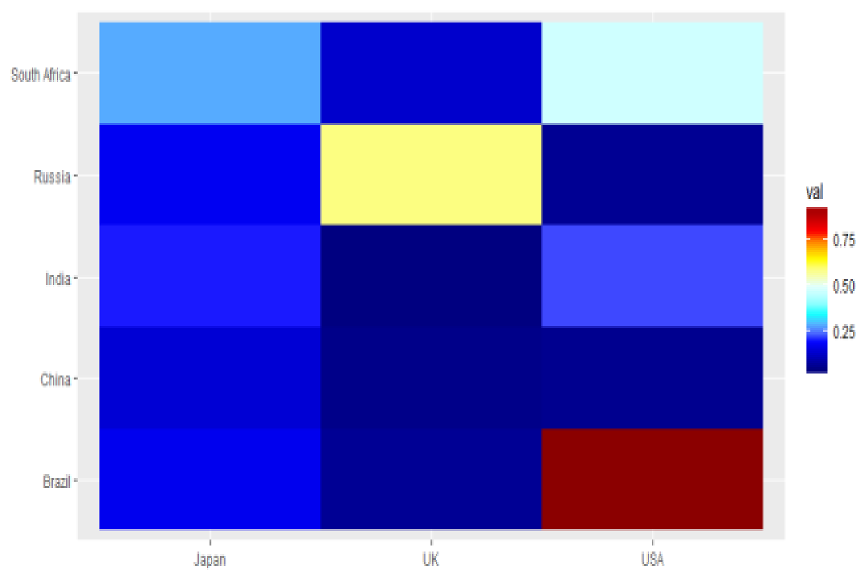
The varying correlation level by the different BRICS markets with developed countries shows that the BRICS countries do not appear as a group in terms of their correlation with developed countries markets. This evidence is in favor of H2. For our third hypothesis, we find a mixed evidence. Proximity between USA and Brazil and high degree of correlation between the two gives evidence in favor of the H3. While the lack of correlation in the case of Japan and China as also shown by the copula models in the following discussion gives evidence against our H3.

To measure extreme comovement, we utilize the copula approach. We first run the GJR-GARCH model on all the return series to remove the GARCH effects from these series. We then fit the copula models on the de-meaned data. We use the t-copula to measure symmetric tail dependence while we use the Clayton and Gumbel copulas to measure the positive and negative asymmetric tail dependence. To visualize the relationships between variables, we display the results of copula models in the form of heat maps. This will also keep the analysis in line with the graphic depiction of the wavelet coherence analysis. Heat maps are accompanied by the color scale that describes the strength of tail dependence measures. Red color represents a strong tail dependence while the blue color represents the weak tail dependence.

t- copula



Clayton copula



Gumbel copula

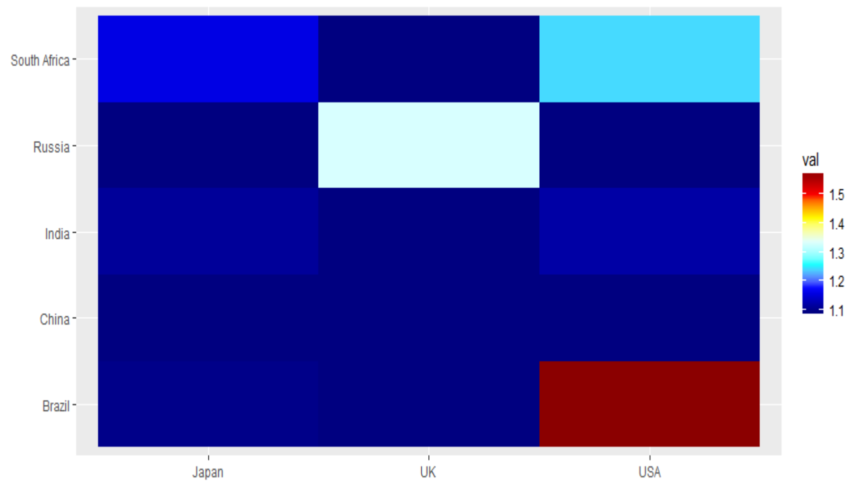
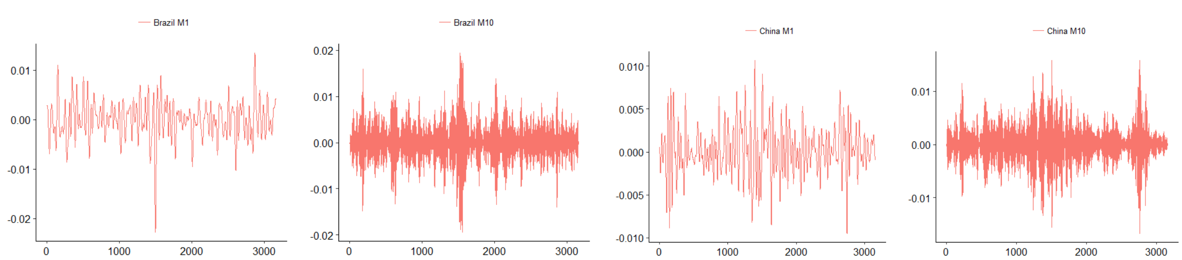


Figure 3: Heat maps of the three copula models for the raw series returns. The coefficients of correlation from the copula model are presented in tabular form in the appendix of the paper as well.

Figure 3 shows the tail dependence parameters for all three copulas for the raw series return residuals from the GJR-GARCH model in the form of a heat map. The results validate the results from the wavelet analysis. Brazil shows the highest tail dependence with the USA in all the three copulas. While China shows the least tail dependence with all the three developed countries in all three copula families. We next use the VMD (Variational mode decomposition) to decompose the raw return series into ten modes set arbitrarily. M1 and M10 modes for each series are given in figure 4.



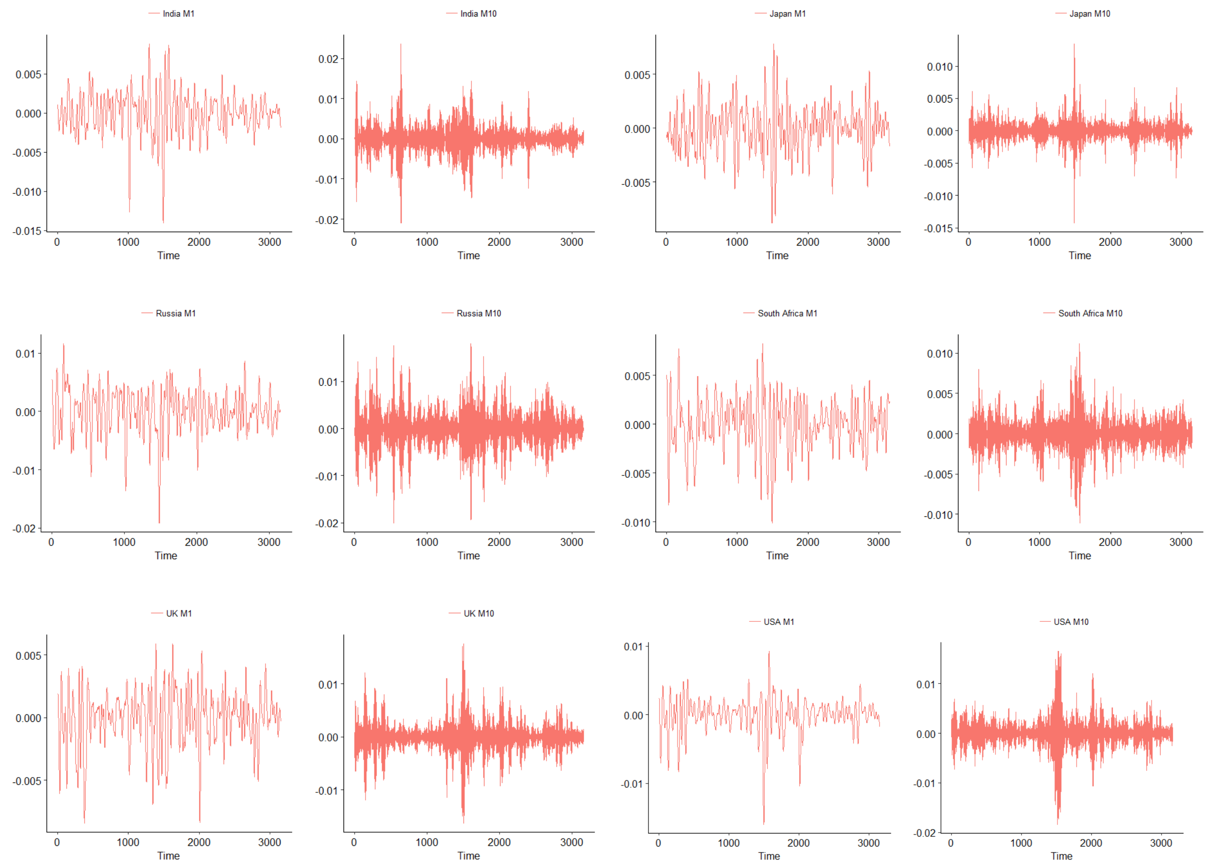
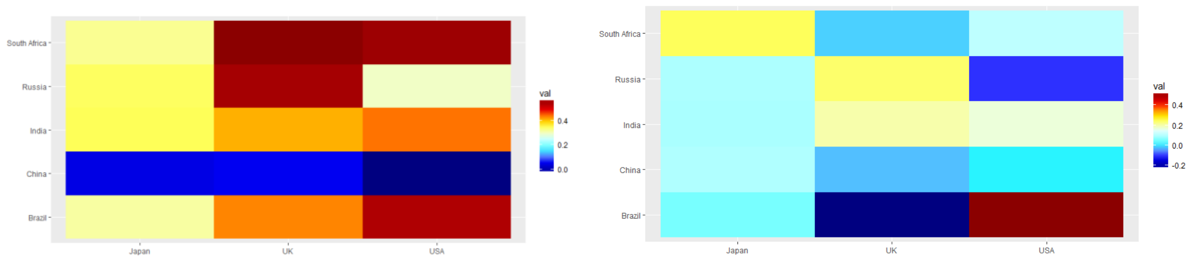


Figure 4: M1 and M10 graphs of the raw return series for all the eight countries in our dataset.

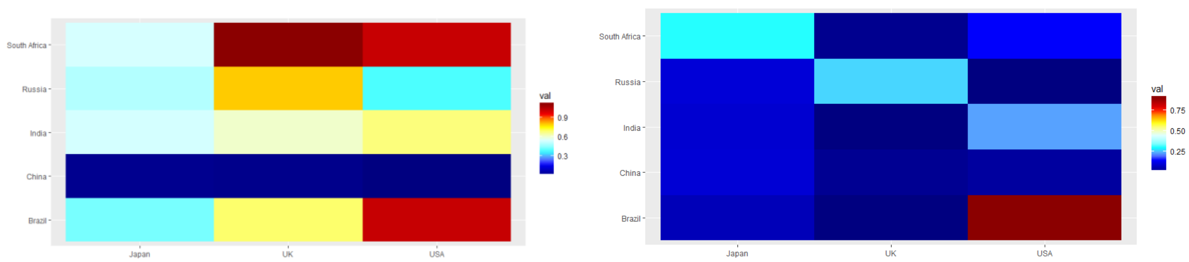
According to Mensi et al. (2017), the M1 series represents the long term dynamics of the data while M10 shows the short term dynamics of the data. We next fit the copula models on M1 and M10 series separately in figure 5 to check the tail dependence in the long run and the short run respectively. We see that for all three copulas the M1 series produces heat map with reddish and yellowish color while M10 series produces heat maps with bluish colors for all the country pairs except the USA-Brazil pair which shows strong tail dependence both in the short run and long run and for all the copula families. It means that the USA and Brazilian markets are correlated both in the short run and the long run. This result is similar to that obtained from the wavelet analysis. Also, all the country pairs seem to have a lower correlation in the short run than in the long run. The results also confirm that the Chinese market has the lowest correlation with all three developed markets.

t-copula M1 t-copula M10



Clayton copula M1

Clayton copula M10



Gumbel M1

Gumbel M10

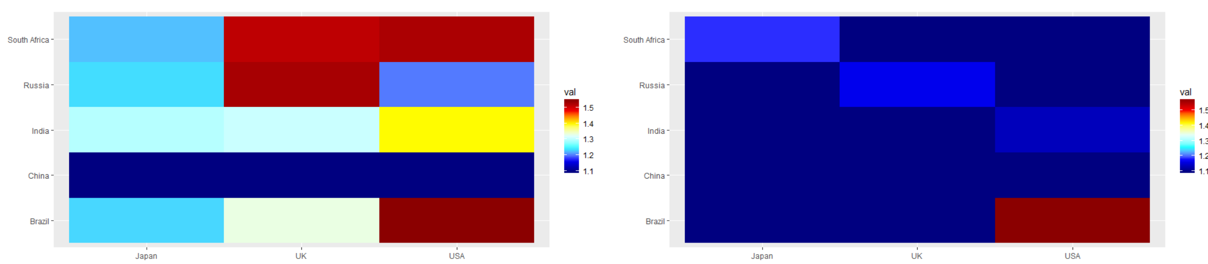


Figure 5: Heat maps of the three copula models for the M1 and M10 series. The coefficients of correlation from the copula model are presented in tabular form in the appendix of the paper as well.

5. Discussion

The results from analysis need further discussion. Our results provide evidence to answer our main question of interest, whether BRICS are good investment opportunity for portfolio diversification. Previous literature has mixed findings, which country amongst BRICS has most correlation and which has a least correlation with developed economies. Some studies are of the view that there is strong co-movement between the US and China and hence China is not good diversification option Bekiros (2014). On the contrary, Lehkonen and Heimonen (2014) and Syriopoulos et al. (2015) find that the diversification option across developed markets and China present a good opportunity for the investors. Our results add further evidence to their argument. Our results are also in line with Zhang et al. (2013) who find that the 2007-09 GFC has altered the correlation structure among the BRICS and developed countries. Russian and Brazil financial markets have stronger correlations with developed countries markets` than Indian and Chinese markets. Our results are different from Das et al. (2018) who report weaker contagion in Latin American emerging markets. Yarovaya& Lau (2016) report that the stock market co-movements between UK and the BRICS countries' equity markets. The results suggest diversification is more beneficial when investments are made in Chinese stock market. Our study reports similar results with our proposed methodology. Another insight from the results is that although BRICS is a group of countries with many similar characteristics they may not be considered to homogeneous group for portfolio diversification purposes.

The two approaches used in our paper, wavelet and vmd copula give consistent results about the correlation between developed and developing country pairs. This shows that our main results are robust to the change in methodology. Another result discussed in the paper is about the increase in the inter-connectedness of the sample firms after the Global Financial Crisis (GFC). To give further support to this test we run a simple test (given in appendix B) that checks the correlation between developed and developing economies using interaction terms. The significance of the positive relationship between developed and developing markets on the post crisis interaction term shows that the relationship between the countries has increased after the crisis, suggesting increased contagion between the developed-developing countries after the global crisis. This is consistent with the earlier results, showing robustness of the results.

6. Conclusion

This paper studies the developed countries – BRICS countries comovement pairwise using WSC approach and VMD-copula approach. In general, the results obtained about the short run and long run co-movement have important policy repercussion, which will be further elaborated in the following discussion.

Not all BRICS countries co-move with the developed countries, stocks with the same intensity. Brazil stock market shows strongest co-movement with the USA stock market while the Chinese stock market shows least co-movement with either of three developed stock markets. The difference in the comovement of the BRICS countries' stock may be due geographical orientation of the markets. This is supported by the results in the study. USA and Brazil commove most amongst other market pairs. This may be because of the geographical proximity of these two markets. One result of the wavelet analysis is that developed countries' stocks are leading, while BRICS countries' stocks are lagging in their co-movement with developed countries. Through VMD based copula tests, we again find that tail dependence, in the long run, is stronger than in the short run. Only the Brazilian market shows strong tail dependence in the long run and short run alike. Brazilian stock market co-moves with the USA stock market in the short run, which shows that there is a strong contagion effect from the USA market to the Brazilian market. The Chinese market has a very low correlation with either of the developed countries` markets. Investors in these markets can look to invest in the Chinese market for diversification purposes. Any portfolio consisting of Chinese stocks and developed countries` stocks will minimize the risk of the portfolio and thereby minimize any loss in case of a shock to the developed countries` markets. There appears to be the emergence of red areas in the low coherence graphs around the time of the Global financial crisis. This shows that markets co-move during the time of financial crisis, and then after the crisis, this co-movement disappears. Our results provide new evidence for the discussion that which of the emerging markets are better portfolio diversification options for investors in the developed markets. We find that Chinese market is a better diversification option for investors in the developed markets for the reasons analyzed above.

Our results should be interpreted cautiously as we report correlations that can not be taken as causal factors. The empirical methodology that we employ does not use p-values for presentation of results. Therefore, our study might not be directly comparable to many of the other studies due to above reasons. Future empirical work can look into the characteristics of the BRICS that cause a very high or low level of correlation with the developed markets. That will allow global investors to make more accurate portfolio choices and government and policy makers to adopt better policy choices. By knowing the nature of comovement between developed – emerging countries pairs of markets will allow investors to better diversify their investments and calculate risk-return more accurately.

Abbreviations

BRICS	Brazil, Russia, India, China and South Africa
GFC	Global Financial Crisis
VMD	Variational mode decomposition
DCC	Dynamic conditional correlation
WCA	Wavelet coherence analysis
DWT	Discrete Wavelet Transform
CWT	Continuous Wavelet Transform
WSC	Wavelet squared coherence

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Appendix: A

These tables present the correlation coefficients of copula models presented in the figure 3and 5 of the paper for ease of interpretation of results.

T-copula (Raw series)

	Japan	UK	USA
South Africa	0.21	0.12	0.35
Russia	0.15	0.43	0.10
India	0.15	0.08	0.17
China	0.12	0.09	0.09
Brazil	0.15	0.08	**0.67**

Clayton-copula (Raw series)

	Japan	UK	USA
South Africa	0.23	0.13	0.38
Russia	0.12	0.45	0.12

India	0.13	0.09	0.19
China	0.14	0.11	0.11
Brazil	0.18	0.12	**0.77**

Gumbel-copula(Raw series)

	Japan	UK	USA
South Africa	1.13	1.13	1.25
Russia	1.12	1.35	1.12
India	1.13	1.09	1.19
China	1.14	1.11	1.11
Brazil	1.18	1.12	**1.65**

T-copulaM1 T-copula M10

	Japan	UK	USA	Japan	UK	USA
South Africa	0.41	0.42	0.65	0.20	0.11	0.31
Russia	0.35	0.63	0.30	0.12	0.40	0.10
India	0.15	0.48	0.27	0.15	0.08	0.17
China	0.09	0.09	0.09	0.12	0.09	0.09
Brazil	0.35	0.38	**0.77**	0.15	0.08	**0.72**

Clayton-copula M-1 Clayton-copula M-10

	Japan	UK	USA	Japan	UK	USA
South Africa	0.23	0.13	0.38	0.23	0.23	0.18
Russia	0.12	0.45	0.12	0.22	0.25	0.22
India	0.13	0.09	0.19	0.18	0.19	0.19
China	0.14	0.11	0.11	0.10	0.11	0.11
Brazil	0.18	0.12	**0.77**	0.18	0.12	**0.79**

Gumbel-copula M-1 Gumbel-copula M-10

	Japan	UK	USA	Japan	UK	USA
South Africa	1.13	1.53	1.45	1.11	1.13	1.21
Russia	1.12	1.65	1.42	1.11	1.20	1.12
India	1.13	1.09	1.19	1.12	1.09	1.11
China	1.14	1.11	1.11	1.11	1.10	1.10
Brazil	1.17	1.13	**1.72**	1.18	1.12	**1.75**

Appendix: B

Table: A simple structural break test to check the post and pre crisis correlations between developed and developing economies pairs. Pre and Post are dummy variables which indiacate pre-crisis and post-crisis periods respectively. The interaction terms depict the effect of the pre and post on the relationship (correlation) between the developed and developing economies.

			US					UK			
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1
	BRAZIL	RUSSSIA	INDIA	CHINA	SOUTH AFRICA	BRAZIL	RUSSIA	INDIA	CHINA	SOUTH AFRICA	BRA
	0.548***	0.289***	0.0004	0.00246	0.234	0.0039***	0.289***	0.0005	0.00150*	0.0126**	0.18
Market Ret	(17.75)	(9.66)	(0.62)	(1.61)	(1.29)	(6.50)	(9.66)	(0.01)	(2.21)	(2.09)	(4.4
Post*	0.218***	0.003	0.0023**	-0.00153	0.236***	0.306***	0.002	0.0044***	-0.000088	0.586***	0.092
MarketRet	(5.90)	(0.37)	(3.07)	(-0.97)	(9.59)	(17.80)	(0.09)	(10.72)	(-0.11)	(26.29)	(2.7
Pre*	-0.259***	0.005	-0.0061	-0.00297	0.137	0.053	0.0431	0.0014	-0.00150*	0.31	-0.10
Market*Ret	(-7.39)	(1.09)	(0.65)	(-1.79)	(0.61)	(1.27)	(0.91)	(0.39)	(-2.21)	(0.14)	(-2.1
N	3907	3864	3788	4221	3970	4315	3933	3870	4336	3972	378

t-statistics in parentheses $^{*}p< 0.05$, $^{**}p< 0.01$, $^{***}p< 0.001$