Analysing time varying co-movements among the US and BRICS stock markets

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Abstract: We perform a three dimensional analysis of the co-movements between developed US market and the emerging BRICS markets through wavelet coherence. This analysis identifies the extent to which each of the BRICS markets provide portfolio diversification opportunities for international investors. We find evidence of a highly heterogeneous degree of co-movement of the US and each of the BRICS markets that vary based on investment horizon. Our findings reveal that Brazil and South Africa have the highest degree of co-movement at higher frequencies or trading period up to a week followed by India (above one month) and Russia (above four months). China has the least co-movement for duration less than a year. The results indicate that effective portfolio diversification decisions are sensitive to both frequency and duration. The strong co-movement at a particular time scale implies that investors must make optimal trade-offs to reap the benefits of portfolio diversification and duration diversification.

Keywords: BRICS Stock market; co-movement; continuous wavelet transform; CWT; wavelet coherence; WTC; time scales.

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1 Introduction

Investing in emerging equity markets has become popular in recent years due to the possibility of higher rates of return triggered by economic growth. However, at the same time, emerging markets are highly vulnerable, have asymmetric behaviour to positive and adverse global developments and during bull, and bear trends. Based on these changing correlations, international investors need to re-balance +/3sz their portfolio in these markets (Mensi et al., 2017). Hence, it becomes pertinent to understand the changing relationships from multiple perspectives like time, frequency and duration of investments among other factors, to amend portfolios and gain out of effective diversification strategies. The BRICS, (i.e., Brazil, Russia, India, China and South Africa) countries have emerged as the best epicentre for international investors. The economic performance of these countries has been impressive in the last decade. These countries have made a critical transition from being 'developing countries' to 'emerging markets'. The BRICS countries are distinguished from other emerging markets by their demographic and economic potential. As of 2015, the five BRICS countries together comprised more than a quarter of the world's land area, more than 42% of the world's population and around 22.53% of global GDP. The BRICS economies aligned with the global economy through trade and financial activities. In terms of GDP growth, demographic indicators, international trade, FDI inflows and outflows, BRICS economies optimise their significance as an international economic player. The current and potential growth rates of the BRICS countries have significant implications for the capitalisation of their stock markets and for their financial dependence on other stock markets. This implies that, BRICS nations are projected to grow in their equity market. Further, globalisation and development of information technology have become prominent factors that determine worldwide changes in stock prices and have made international stock markets more correlated. This emphasised a gap, which provokes us to explore the stock market relationship in the context of developed and emerging economies.

In this paper, we contribute to the literature on co-movements of developed (USA) and emerging (BRICS) markets by analysing its dynamics in the time-frequency domain. An extensive body of financial literature focused on the relationships between international equity markets. Co-movements between the Moroccan stock market and the USA, France, UK and Germany stock markets was analysed (Ghini and Saidi, 2015) by applying flexible multivariate GARCH models, namely constant conditional correlation (CCC) and dynamic conditional correlation (DCC), to measure conditional correlations between the stock markets. Jalloh (2016) employs a dynamic panel approach to examine the impact of market capitalisation on economic growth in Africa. The findings demonstrate that stock markets are potential avenues for accelerating economic growth. Majority of the economic time series analysis is carried out either in the time or frequency domain and fail to capture the persistence effect. These three aspects are pooled into a three-dimensional framework as Wavelet analysis. Niţoi and Pochea (2020) investigated the dependence patterns in 24 European equity markets and the effect of investor sentiment on markets correlations. The results revealed heterogeneity in the time-varying dependence and across markets. Another study by Ameur and Louhichi (2021) explored the Impact of Brexit on the interdependence of the UK and European stock markets using GARCH framework and ADCC-GARCH model. During this time, volatility, and overall spill over was increased indicating that European economic disintegration leads to a fall in European financial market integration. The net flow-return relationship and the trading behaviours of foreign investors in South Korea with respect to economic uncertainty were analysed (Baba and Sevil, 2021) by employing TVP VAR Models. Due to informational disadvantage, the findings exhibit that international investors in the South Korean equity market do not naively pattern trading behaviour. As a result, the claim that foreign investors lack local knowledge is proven false.

Previous Literature reported the importance of wavelet-based approach across different markets. Shik Lee (2004) explored the dynamic price transmission and volatility spill over effects of US and Korean stock index using the discrete wavelet decomposition. The findings revealed that the developed market influences the emerging market, but not vice versa. Ranta (2013) studied the contagion between Germany, UK, US and Japan from 1984–2009. The author reported that co-movements among the developed markets have been at a consistent level over longer time horizons, while the co movements increased in shorter period of time, particularly during the financial crisis. Similarly, Aloui et al. (2014) investigated the short term and long-term dependencies between stock market returns for the Gulf Cooperation Council (GCC) Countries using WTC analysis during the period 2005–2010. Particularly after the 2007 crisis, the authors found a shift in co-movement dynamics and a higher degree of co-movement persisted during the post-crisis period. More recently, Das and Manoharan (2019) studied the contagion and co-movement in South Asian markets vis., India, Pakistan and Sri Lanka by applying wavelet based methods. The findings revealed that the state of contagion is non-existent during the crisis period and lesser co movement among the markets.

Moreover, a growing number of studies use wavelet-based methods to investigate different perspectives on financial markets. Vacha and Barunik (2012) studied the dynamic correlations based on WTC between crude oil, heating oil, gasoline and natural gas for the period November 1, 1993 to July 21, 2010.The results exhibited that some energy pairs indicate strong dynamics in co-movement in time during different investment periods. The linear and nonlinear Granger causalities between oil price and the exchange rate of the Indian currency were investigated using granger causality, artificial neural networks and wavelet methodology (Tiwari et al., 2013). The findings highlighted the existence of causal relationships between the oil price and the exchange rate at higher time scales (lower frequency). The interdependence and causality relationship between oil and East Asian stock returns was analysed using WTC analysis. The results revealed that in the long run, oil prices lead stock returns. The co-movement between crude oil price and the exchange rate markets of oil importing/exporting countries were analysed using the WTC framework (Yang et al., 2017). The results suggested the non-existence of relationship between the returns of the crude oil price and the exchange rates for the oil-exporting countries and vague relationships for the oil-importing countries. Similarly, co-movements among gold futures and the spot market were scrutinised (Jena et al., 2017) by employing wavelet approaches. The findings of the study exhibited positive relationship among gold futures and the spot market. Meng (2018) used wavelet analysis to explore the volatility patterns between commodity prices and crude oil prices. Tiwari et al. (2019) applied WTC to analyse the relationship between energy indices for fuel price, food price, industrial inputs price, agriculture raw material price, metal price and beverage price and identified significant phase-based patterns in the co-movements.

Some literature has also studied the wavelet framework in several new dimensions like oil market speculators' expectations (He et al., 2009), exchange rates (Boubaker and Boutahar, 2011), Gulf stock markets (Masih et al., 2010), Eurozone stock markets (Fernández-Macho, 2012), financial data mining (Sun and Meinl, 2012), hedging across oil and stock markets (Khalfaoui et al., 2015), co-movement of oil price and exchange rates in Pakistan market (Shahbaz et al., 2015), co-movement between oil price and automobile stock return (Pal and Mitra, 2019), US housing and stock markets (Liow et al., 2019), co-movement of COVID-19 and Bitcoin (Goodell and Goutte, 2021), nuclear energy consumption and economic growth in the UK, (Kirikkaleli et al., 2021) and COVID-19 pandemic waves and global financial markets (Karamti and Belhassine, 2021).

Applying the continuous wavelet transform (CWT) approach is largely significant for its ability to allow assessment of the scale-dependent, nonlinear synchronisation across markets both over time and in different frequencies. Certainly, the time-varying linear/nonlinear phase-dependent associations together with the higher order effects are completely captured by the WTC analysis. The wavelet multi-scale analysis of co-movement capture potential nonlinear linkages between the markets overcoming simultaneously, the inadequacies about linearity of parameters, short length of frequency bands and threshold limit based on input variable frequency (Breitung and Candelon, 2006). To analyse the issue in detail, this study decomposes the time-frequency relationship between US-BRICS through a CWT and wavelet coherence (WTC) approach. From a practical perspective, short-term investors are concerned with interim price variations, while long-term participants alter their investment decisions based on the long-term price movements. The findings reveal the variations in the co-movements and the heterogeneity of market participants and their investment horizons in BRICS stock markets. Further, among BRICS markets Chinese market has the least co-movement with US for short-term investment horizon up to one year. Our findings are consistent with

Jiang et al. (2013) who find that Chinese investors derive maximum portfolio diversification benefits by investing in developed stock markets.

This paper is structured as follows. After a brief introduction to wavelets, Section 2 introduces the data and presents the WTC used for the estimation of the relationship between two series in time and across scales. Section 3 provides results of the empirical analysis. Finally, conclusions are provided in Section 4.

2 Data source and methodology

The study investigates the co-movement of emerging (BRICS) markets with developed (USA) markets for the period January 2, 2002 to March 31, 2019 (3,635 trading days) by employing CWT. The dataset comprises of daily closing index values of prominent benchmark market indices (vis., NYSE, IBOVESPA, CNX NIFTY, SSE Composite, JSE) of US-BRICS countries from Bloomberg database.

The wavelet transform has been beneficial for analysing the non-periodic, noisy, intermittent and transient signals. It uses little wave like functions called as wavelets. Wavelets are used to transform the signal under exploration into another representation, which presents the signal information in a more useful form. It provides a three-dimensional figure that demonstrates time series information at different frequencies, time and strength. The frequency might fluctuate from low to high; the time may vary from short term to long term and finally, the strength of association is computed by colour coding (Grinsted et al., 2004). Primarily, we employ CWT to remove noise in the series and then the pattern of co-movement is analysed using WTC.

2.1 Continuous wavelet transform

A wavelet is a function with zero mean and that is confined in both frequency and time. The continuous wavelet framework is summed up for a bivariate case to study the relationship between two series in time and across scales. CWT is utilised to remove the noise in the series. The CWT of a time series (n = 1, …., N) with uniform time steps δt is the convolution of xn with the scaled and normalised wavelet, is characterised as:

$$w_n^x(K) = \sqrt{\delta t / k} \sum_{n=1}^{N} x_{n'} \varphi 0 \left[(n' - n) \frac{\delta t}{k} \right] \tag{1}$$

The wavelet power is defined as $\left| w_n^x(K) \right|^2$. The complex argument of $\left| w_n^x(K) \right|$ v can be inferred as the local phase. Since the wavelets are not totally limited in time, CWT has edge impact which is tended by presenting cone of influence (COI), which eliminates edge impacts. The statistical significance level of the WTC is assessed utilising Monte Carlo methods (Torrence and Compo, 1998). The statistical significance of wavelet power is assessed in respect to the null hypotheses that the signal is created by a stationary process with a given background power spectrum (ps). The corresponding distribution for the local wavelet power spectrum at each time n and scale k as follows:

$$M \left(\frac{\left| w_n^x(K) 2 \right|}{\sigma_{x^2}} < p \right) = \frac{1}{2} psx_v^2(p) \tag{2}$$

2.2 Wavelet coherence

WTC is utilised as a tool to find the relationships between two series. The relationship is found through the frequency bands and time intervals. The WTC is viewed as a confined correlation coefficient in the time frequency space. Torrence and Webster (1998) characterised the WTC of two time series as:

$$L_n^2(K) = \frac{\left|K\left(k^{-1}w_n^{xy}(k)\right)\right|2}{\left|K\left(k^{-1}w_n^{x}(k)\,|\,2\right).\right|K\left(k^{-1}w_n^{y}(k)\,|\,2\right)} \tag{3}$$

where K is a smoothing operator and $L_n^2(K)$ is the estimation of wavelet squared coherency. The numerator and the denominator explain the squared absolute value of the smoothed cross-wavelet spectrum and the smoothed wavelet power spectra, respectively.

3 Empirical analysis

3.1 Descriptive statistics

Table 1 report the descriptive statistics of six Stock Market Indices vis., NYSE, BOVESPA, MICEX, NIFTY, SSE and JSE. The sample period is from January 2, 2002 to March 31, 2019. According to the Jarque-Bera normality test, it is evident that all the variables under study are not normally distributed. It is observed that the mean returns are positive for all variables. The variables like NYSE, BOVESPA, MICEX, NIFTY are skewed left and leptokurtic. Excess Kurtosis of over 3 is found in SSE which indicates presence of fat tails. Figures 1–6 provide the graphs indicating the movement of US-BRICS indices for the sample period.

Figure 1 Movements of US stock indices (2002–2019) (see online version for colours)

Table 1 Descriptive statistics

	NYSE	*BOVESPA*	*MICEX*	*NIFTY*	*SSE*	*JSE*
Mean	8,421.35	47,843.54	1,328.56	5,013.47	2,497.07	28,293.79
Median	8,296.97	52,203.00	1,440.99	5,187.95	2,357.71	27,475.40
Maximum	11,661.22	73,517.00	2,285.43	9,173.75	6,092.06	49,333.00
Minimum	4,267.60	9,995.00	302.18	924.30	1,011.50	6,763.72
Std. dev.	1,765.19	15,850.69	468.87	2,254.78	945.28	12,584.78
Skewness	–0.1231	–0.7369	–0.6291	–0.0333	0.8774	0.0363
Kurtosis	2.0140	2.5396	2.4176	2.0501	4.0136	1.8449
Jarque-Bera	139.20	321.35	259.08	122.22	553.51	180.56
Observations	3,635	3,635	3,635	3,635	3,635	3,635

Figure 2 Movements of Brazil stock indices (2002–2019) (see online version for colours)

Figure 3 Movements of Russia stock indices (2002–2019) (see online version for colours)

Figure 4 Movements of India stock indices (2002–2019) (see online version for colours)

Figure 5 Movements of China stock indices (2002–2019) (see online version for colours)

Figure 6 Movements of South Africa stock indices (2002–2019) (see online version for colours)

Figure 7 Co-movements of US-Brazil index (see online version for colours)

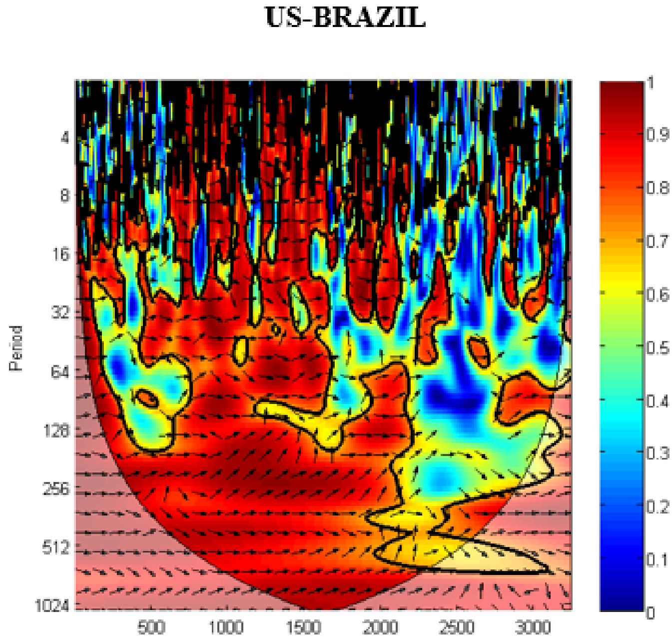


Figure 8 Co-movements of US-Russia index (see online version for colours)

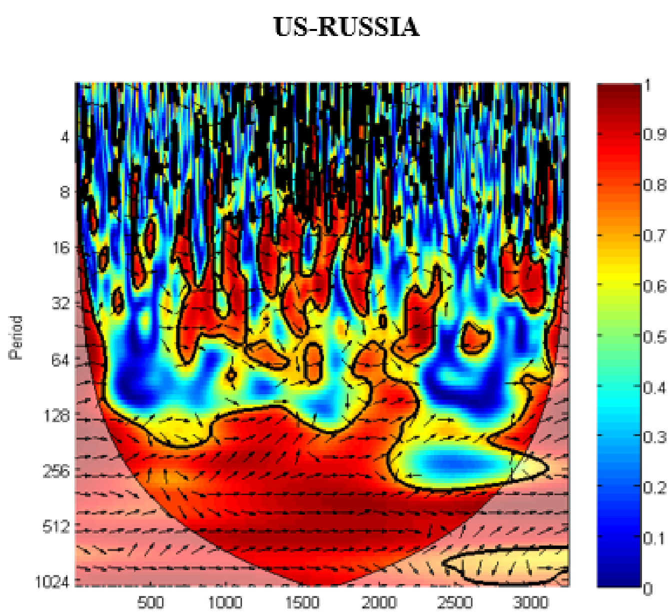


Figure 9 Co-movements of US-India index (see online version for colours)

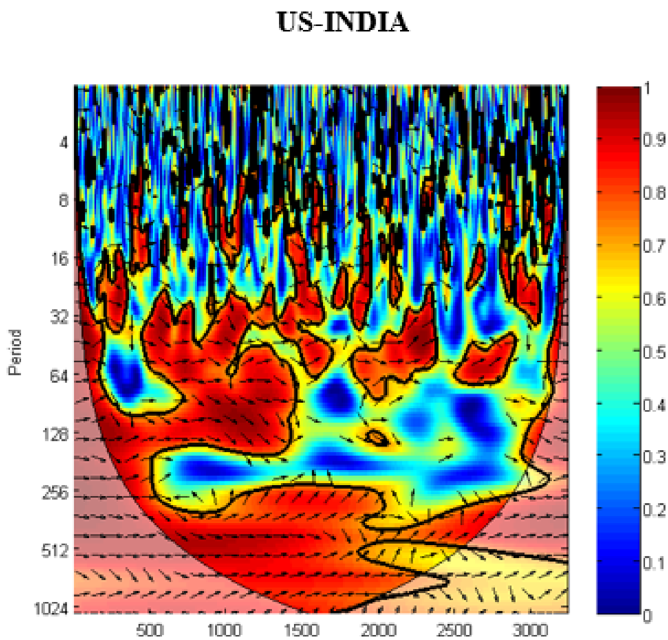


Figure 10 Co-movements of US-China index (see online version for colours)

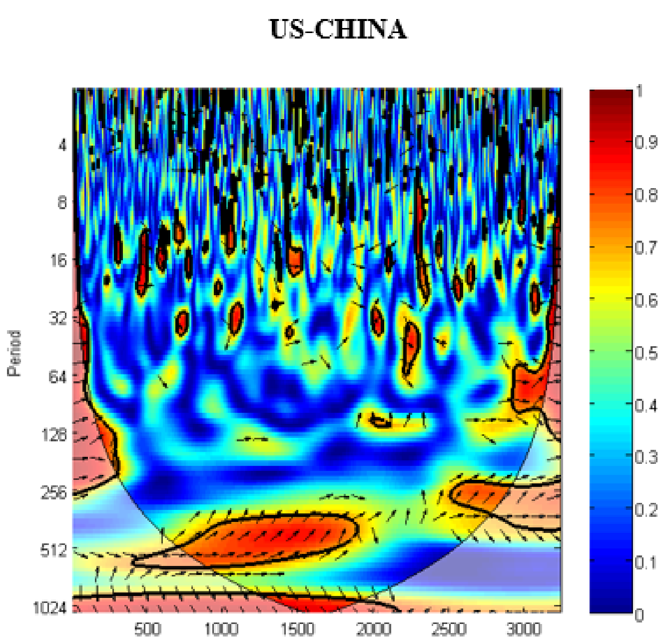
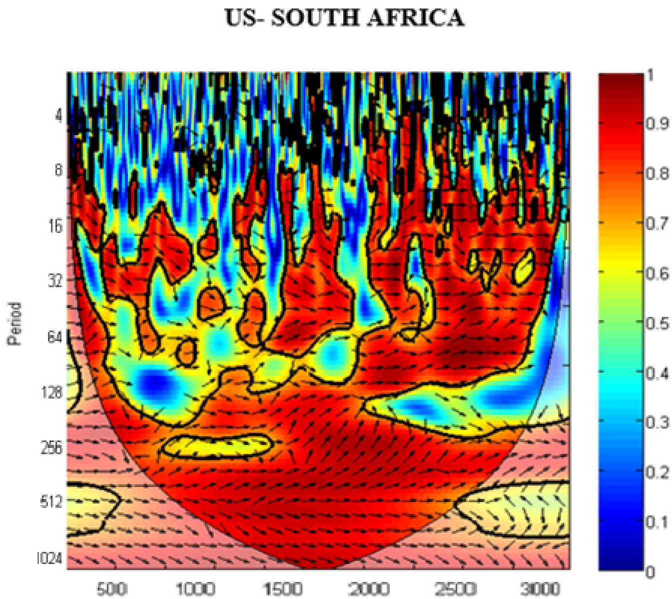


Figure 11 Co-movements of US-South Africa index (see online version for colours)



Notes: In Figure 7–11, the colour code for the wavelet spectrum ranges from blue to red; i.e., from low (0) to high (1). The thick black contour lines denote 5% statistical significance calculated from Monte Carlo simulations. The thin black lines that border the COI indicate edge effects and region outside COI do not have any statistical significance. The phase arrows indicate in-phase (pointing right) and anti-phase (pointing left) co-movements between each of the BRICS markets with US stock market. Additionally, lead/lag effects are also indicated through the direction of the arrows. Arrows that point left upward/right downward are periods when BRICS markets lead and arrows that point left downward/right upward are periods when US market leads.

Table 2 WTC axis

X-axis		*Y-axis*	
Observation	*Corresponding time*	*Period*	*Corresponding frequency*
1 (First)	1st December 2002	4	4 days
500	3rd May 2005	8	8 days
1,000	24th August 2007	16	16 days
1,500	11th January 2010	32	32 days
2,000	2nd May 2012	64	64 days
2,500	1st May 2014	128	128 days
3,000	26th April 2016	256	256 days
3,500	20th June 2018	512	512 days
3,635	29th March 2019	1,024	1,024 days

Note: Table 2 provides the time and frequency details corresponding to x-axis and y-axis in the WTC plots in Figure 7–11.

3.2 WTC results

The CWT based WTC plots along with phase differences of BRICS-US markets are represented in Figures 7–11 respectively. In all the figures, x-axis (horizontal) represents the trading days for the period from 1 December 2002 to 31 March 2019, and y-axis (vertical) refers to the investment horizon in scales ranging from one day to 1,024 days. The colour codes in the images range from blue to red with blue representing low coherence (correlation near zero) to red indicating high coherence (correlation near 1). The thin black curved line represents the statistically significant region (at 5% significance level) obtained through Monte Carlo simulations. Arrows indicate the phase differences as follows: arrows pointing right-in-phase; left – anti-phase; right and up – first series lagging; right and down – second series lagging; left and up – first series leading; and left and down – second series leading. In all the plots, US market returns are made as the first series to maintain consistency in interpretation.

Table 3 WTC phase differences

Direction of arrows in WTC plots	→	↘	↗	←	↖	↙
Effects in Figures 7–11	In-phase (Cyclical effect)	US lead and BRICS lag	US lag and BRICS lead	Anti-phase (Anti-cyclical effect)	US Lead and BRICS lag	US Lag and BRICS lead

Note: Table 3 provides interpretation for the phase effect arrows in the WTC plots in Figure 7–11.

The results are interpreted based on the scales of investment horizon starting from very short holding periods of 2–4 days/4–8 days to as high as 1024 days or nearly four years (considering active trading days). On a relative comparison of co-movements of each of the BRICS markets with the US market, we generally find that correlations with the US market appear to be strongest for returns of Brazil index followed by South Africa in shorter horizons of 2–4 days and 4–8 days. While Russia and India seem to be weakly correlated in higher frequencies or shorter investment periods up to eight days, China has almost no correlation with the US market for stock holding period up to eight trading days. The results indicate that among BRICS markets, Chinese markets serve as the best destination for portfolio diversification opportunities for very short speculative trading durations of less than 8 days followed by Russia and India as viable options.

On observing investment horizons of 8 and 16, 16 and 32, 32 and 64 days, we found higher coherence of Brazil, South Africa and India (beyond 32 days) with the US index with the exception of Chinese and Russian markets where correlations were very low. One striking similarity is during 2007–2009 global financial crisis period where BRICS markets except China showed relatively greater overlaps in co-movements with USA. The higher degrees of coherence in returns at higher frequencies or shorter investment horizons is associated with contagion hypothesis that results in structural breaks in asset prices due to external shocks (Aloui and Hkiri, 2014). On observing time scales of 32–64 days, we find that correlations between US-BRICS markets except China is relatively stronger compared to scales of 1–4, 4–8 and 16–32 days that constitute the short-term investment horizon from a single day up to two-three months. In the medium-term holding periods of 64–128 and 128–256 trading days, the co-movements of Brazil, South

Africa and India grow stronger. Russian markets exhibit a higher co-movement for trading periods beyond 128 days. The correlations of Chinese market with USA continue to remain low for investment periods up to 256 days or one year. The phase arrows indicate that wherever stronger correlations are observed, the movements of the indices are in-phase, exhibiting cyclical co-movements.

Our results indicate that the co-movements between USA and each of the BRICS stock markets manifest in the long run, that is for investment period beyond a year. The short-run co-movements up to eight trading days are high for Brazil followed by South Africa implying a high degree of integration of Brazil and South Africa with US markets. Among all the BRICS markets, China has the least degree of integration for investment horizon up to 256 trading days and thus serves as the best portfolio diversification destination. Indian market appears as a viable diversification option for the medium term up to 32 trading days. Russia enables effective diversification opportunities up to 128 trading days. The findings convey the presence of strong degree of correlation among the US-BRICS markets in the long run especially between 512 and 1,024 days. Indeed, the degree of integration among global markets has manifested in the recent years implying increased interdependence especially during periods of distress.

4 Conclusions

In the present study, we investigate the evolution of nexus between developed and emerging stock markets, considering the US-BRICS countries from 2002–2019. Many studies have predicted that BRICS markets provide portfolio diversification opportunities for international investors. However, there is considerable amount of ambiguity regarding the frequency and time horizon that is best suited for diversification. Therefore, the present study performs a three-dimensional WTC analysis that considers the frequency, duration and the degree of co-movements between the markets under study. The WTC findings of the present study are supportive of the fact that the degree of integration in the stock market indices has increased considerably since the financial crisis especially in higher frequencies or shorter investment horizons. This implies increased contagion effect as a shock in one region transmits swiftly to other regions with a high degree of persistence. Among BRICS markets, China has the least co-movement with US market and serves as the best destination for investment duration up to one year. Brazil and South Africa have the highest degree of co-movement at higher frequencies or trading period up to a week followed by India for duration exceeding one month and Russia for duration exceeding four months thereby providing relatively lower diversification opportunities. Overall, the wavelet analysis has contributed in understanding the nexus across developed and emerging equity markets across several investment horizons and periods. The findings provide potential implications for portfolio managers working in the BRICS region to contemplate co-movement through both frequencies and time when designing their portfolios. This would be beneficial for prediction regarding international portfolio diversification with different investment horizon.

Conclusively, our research opens several new avenues for exploratory studies. First, it would be beneficial to understand co-movements applying the WTC analysis to other asset classes across BRICS markets. Secondly, the structural breaks exhibited in some BRICS stock markets may behave independent of certain global crisis or even be a haven to diversify in times of crises elsewhere. Future research may explore deeper to understand the contagion impact of cross-border capital flows in such situations. Finally, it is intriguing to investigate whether there is contagion effect of shocks at very high frequencies or intraday trading which serves as a promising option for future research.

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