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Revisiting the dynamic relationship between exchange rates and stock prices in BRICS countries: A wavelet analysis

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Abstract

Based on a wavelet analysis, this study investigates the dynamic links between exchange rates and stock returns in Brazil, Russia, India, China, and South Africa (BRICS). The results reveal that relationships between exchange rates and stock returns are positive in the medium and long term, indicating that exchange rates lead stock returns in Brazil and Russia. However, the India index pair has a negative relation, and stock returns lead exchange rates in 64−128-day scales over the periods 2008, 2010−2012, and 2012−2015, while South Africa seems to have a more bidirectional causality; the Chinese index pair did not show any correlation. Further, the findings indicate that the crises had a substantial impact on links among the series. These results have important implications that investors should take into account in frequency-varying exchange rates and stock returns and regulators should consider to develop sound policy measures to prevent financial risk.

JEL classification: F31; D53; C58

Keywords: BRICS; Co-movement; Exchange rate; Stock markets; Wavelet analysis; Wavelet coherence

1. Introduction

Over the past three decades, financial crises have sparked active discussions among academics, practitioners, and policymakers about the relationship between exchange rates and stock markets. One major issue facing international investors is identifying co-movements of stock prices and exchange rates over time and frequency-varying properties. This is because of the adoption of free-floating exchange rates by many countries, which restructured the global financial system and this increased capital inflows and outflows, international economic integration, and diversification efforts (Ndako, 2013; Tsai, 2012). All these have significant implications for formulating precise policy in international portfolios. As a result, financial markets around the world became linked because an adverse shock in one financial market damages other markets quickly through transmission channels.

Exchange rate fluctuations are recognized to have effects on stock prices in either a positive or negative direction. Many events—such as the US subprime crisis in 2007, the global financial crisis in 2008, and the European debt crisis in 2010, which affected exchange rates—had an adverse impact on financial markets. Financial markets in most developed countries suffered substantial losses during those periods (Zolfaghari & Sahabi, 2017), which led to bankruptcies at several financial institutions after bank lending and liquidity collapsed (Caporale, Hunter, & Ali, 2014). From a theoretical perspective, export-oriented firms benefit from currency depreciation because weak currency values allow them to export more goods or services and ultimately raise their stock prices. At the same time, stock prices of importers may decline as their profits fall, which means that currency depreciation has an adverse impact on firms' stock prices (Bahmani-Oskooee & Saha, 2016).

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Nevertheless, questions have been raised about dynamic links between foreign exchange rates and stock markets. Measuring the interconnectedness of exchange rates and stock markets is increasingly recognized as being of paramount importance in terms of practical implications for finance because it involves portfolio management, asset allocation, and risk management. The recent financial turbulence created higher uncertainty in financial markets. Specifically, transactions in leading currencies on foreign exchange markets declined and had an adverse impact on stock returns (Caporale et al., 2014). The existing literature examines the effects of exchange rates on stock returns extensively before and after the global financial crisis and uses various methods, raising doubt about existing econometric estimation methods and the effectiveness of current risk management. Moreover, the present time-series econometric models failed to envisage time and multiscales because of the failure of previous studies to reach consistent results about links between exchange rates and stock returns using these econometric models. They were criticized for being restricted to only one or two scales, namely short and long term. These methods include standard ordinary least squares (OLS), cointegration, and error-correction models, Granger-causality or vector autoregressive methods (VAR), and volatility models such as ARCH and GARCH, which are used in risk management. One of the most sophisticated linear time-series approaches used to estimate cointegration and error-correction models is the autoregressive distributed lags model (ARDL). One advantage of this model is that it combines stationary and nonstationary variables.

Therefore, further understanding of interactions between exchange rates and stock markets has received considerable critical attention among investors, corporate managers, portfolio managers, policymakers, and academics. Moreover, the financial disruptions underlined that the shocks that influence one market can spread immediately to other markets through a channel of contagious effects (Zolfaghari & Sahabi, 2017). Hence, there is an urgent need to address the problems caused by repeated financial crises, calling for a revision of the econometric techniques used to measure uncertainty in financial markets. The main disadvantage of these time-series models is that they have predictive power for only one or two time horizons: the short and the long term. Furthermore, the models failed to address the heterogeneity of investors because financial markets are very complex, with thousands of investors who have no homogeneous investment horizons; rather, they have different investment time horizons, ranging from a few seconds to a few years. For instance, short-horizon investors, such as day traders, tend to speculate, and their transactions are measured by transient situations, such as contagious effects, market sentiment, or elements linked to psychology. At the same time, long-term investors, such as institutional investors invest in pensions as they and follow more strictly macroeconomic principles and are more inclined to engage in investment activity than the short-run investors.

This paper focuses more on recent literature explaining the application of wavelet analysis to stock prices. For instance, Reboredo, Rivera-Castro, and Ugolini (2017) examine the co-movement and causality between stock prices and oil and renewable energy. Unlike our study investigates dynamic links between exchange rates and stock returns in the BRICS countries (Brazil, Russia, India, China, and South Africa). Tsai (2012) investigates the relationship between stock prices and exchange rates, especially in six Asian economies (Malaysia, Philippines, Singapore, South Korea, Taiwan, and Thailand), using a dataset covering the periods January 1992 and December 2009 with quantile regression. Dewandaru, Masih, and Masih (2016) investigate whether the co-movement of European equity markets created contagious or fundamental risk.

This paper makes several contributions to the literature. First, it advances the existing literature by applying a wavelet analysis to study the dynamic links between exchange rates and stock returns. We select wavelet analysis because it is a powerful and robust methodology that uses nonstationarity in financial time series to study their co-movements. Specifically, the paper applies wavelet coherence, which offers time-varying correlations between exchange rates and stock returns for different investment horizons, in contrast to cointegration and VAR restricted to one or two holding periods. Wavelet coherence has a unique advantage, providing regions that show the direction and degree of dependence of exchange rates and stock returns and expose associations between cause and effect over time and frequency. Finally, our findings provide policymakers, investors, and portfolio managers with further insights on international portfolios and monetary and of the links between exchange rates and stock returns. The study follows the wavelet method developed by Grinsted, Moore, and Jevrejeva (2004) to examine co-movements between exchange rates and stock returns.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature; Section 3 describes our methodology; Section 4 describes the data; Section 5 presents and discusses our empirical results; and Section 6 offers our conclusions and research implications.

2. Literature review

2.1. Theoretical motivation

This paper adopts two contrasting theoretical models that explain the connections between exchange rates and stock returns—namely, the theory of good markets (flow-oriented theory) and portfolio balance theory (stock-oriented theory). First, the theory of good markets developed by Dornbusch and Fischer (1980) posits that exchange rates encourage stock returns, which means that the depreciation of exchange rates has a positive effect on stock prices. In this regard, currency depreciation induces demand for firms' exports. Notably, a weak currency makes exports more competitive, which in turn increases demand for exports by foreigners. Exchange rate devaluation also discourages imports because production inputs become more costly. In fact, if imports become expensive, they result in a reduction of sales, which makes firm profit fall and, consequently, stock prices as well. Notwithstanding, depreciation thus drives aggregate demand, which improves the trade balance and real economic growth. In addition, the empirical literature documents that exchange rates have a positive effect on stock returns (Caporale et al., 2014; Ülkü & Demirci, 2012).

Second, the portfolio balance theory proposed by Branson (1983) and Frankel (1983) theorizes a negative relationship between exchange rates and stock prices. It argues that exchange rates depend upon demand for financial assets, such as stocks and bonds. Moreover, the theory underlines that exchange rates are determined by the state of the stock market. For instance, in a bull market, demand for stocks increases, which will raise stock prices. It also signifies favorable expectations of domestic economic growth, which in turn increases interest rates and, thereupon, capital inflows from international investors. As a result, a rise in stock prices strengthens exchange rates, as exchange rates adjust to changes in the demand for and supply of domestic and foreign financial assets needed to diversify portfolios internationally. In addition, the growth in stock values translates into higher wealth at enterprises, which consequently increases their production and sales volume. With respect to stock growth, growth induces aggregate demand, which improves the real economy. Nevertheless, in a bear market, stock prices decline, which causes exchange rates to depreciate. Here, we present some of the empirical studies that test this theory (Caporale et al., 2014; Chkili & Nguyen, 2014; Tsai, 2012; Wong, 2017).

2.2. *Exploring the relationship between exchange rates and stock returns*

The existing literature on dynamic links between exchange rates and stock returns is extensive and mostly restricted to econometric methodologies that use the short or long term. Most studies have mixed results. Some research studies find positive links between exchange rates and stock returns (Bahmani-Oskooee & Saha, 2016; Caporale et al., 2014; Ülkü & Demirci, 2012). Although some document negative relationships (Caporale et al., 2014; Chkili & Nguyen, 2014; Wong, 2017), a few research studies also reveal insignificant links between the series (Alagidede, Panagiotidis, & Zhang, 2011).

Numerous empirical studies document positive relations between exchange rates and stock returns, as follows. Bahmani-Oskooee and Saha (2016) find a significant positive correlation between exchange rates and stock returns, specifically for export-oriented firms. They use monthly data between 1992 and 2012 and a nonlinear autoregressive distributed lag (NARDL) model with a set of countries, namely, Brazil, Canada, Chile, Indonesia, Japan, Korea, Malaysia, and Mexico. Similarly, in the UK, Ülkü and Demirci (2012) report a positive relationship; however, the robustness of the results from exchange rates and stock returns depends upon controlling the effects of stock returns in emerging and advanced countries. They use daily and monthly data, covering 2003 to 2010. They suggest that exchange rates have substantial effects on stock returns in countries that receive net capital inflows from abroad, along with strong local stock markets. In the co-movements, Lin (2012) reveal strong coherence between exchange rates and stock market returns, especially during crises. Diamandis and Drakos (2011) examine exchange rates and stock returns, concluding that a positive relationship exists between them. In addition, these two economic series interacted with US stock market returns using cointegration analysis and multivariate Granger causality tests and monthly data, which range from January 1980 to January 2009. The results show that the US stock market moderates the link between exchange rates and stock prices. Using yearly data from 1979 to 2014 in South Africa and a cointegration estimator, Mitra (2017) indicates that the relationship between exchange rates and stock returns is positive in the long term.

By contrast, Tsai (2012) finds a negative relationship between exchange rates and stock returns. He used a quantile regression and monthly data from 1992 to 2009 for several countries, including Malaysia, Philippines, Singapore, South Korea, Taiwan, and Thailand, and the results document a stronger relationship at extreme points. Bashir, Yu, Hussain, and Zebende (2016) use a detrended cross-correlation estimation to examine the co-movement between exchange rates and stock markets for different investment horizons and Granger causality to confirm the direction of causality for Latin American countries, namely, Argentina, Brazil, Chile, and Mexico. They use monthly time-series data from 1991 to 2015, which indicate that exchange rates and stock returns have a negative relationship in the majority of the selected countries over the short term. Nevertheless, in Argentina and Brazil the relationship was positive over both the short and long term. Additionally, the findings reveal a positive cross-correlation between exchange rates and stock returns in all Latin American countries. Finally, Alagidede et al. (2011) use Granger causality and data covering 1992 and 2005 for five developed countries—namely, Australia, Canada, Japan, Switzerland, and the UK—and their results show no long-term relationship between exchange rates and stock prices. However, the link from exchange rates to stock prices is established by Granger causality in Canada, Switzerland, and the UK, while in Japan the causality is from stock prices to exchange rates.

This variety in results indicates a need to understand the different perceptions of multiscale frequency bands to examine the links between exchange rates and stock returns, rather than a maximum two-scale approach, because little multiscale analysis has been conducted that considers the dynamic relationship between exchange rates and stock market returns using a wavelet approach. The estimation approach mentioned above gives a fresh and deeper understanding of the topic. However, far too little attention has been paid up to now to wavelet analysis, which has multiscale features, providing an opportunity to analyze series at scales with different frequencies (Yang, Cai, & Hamori, 2017), rather than only one or two scales. Wavelet analysis shows an appealing alternative that considers the time and frequency domains simultaneously. In addition, the wavelet model is a very powerful estimator that utilizes signal processing, offering a single chance to examine the co-movements between economic series in the time-frequency dimension. It provides more insights about potential interdependencies at different scales along periods (Ferrer, Bolós, & Benítez, 2016). It outperforms the standard OLS regression, ARDL, Granger causality or VAR, cointegration, and error correction models that are currently the most popular methods for investigating links between the series, and these methods are well-established and dominant in the field.

3. Methodology

3.1. Wavelet analysis

The wavelet model is a very powerful estimator that utilizes signal processing, offering a single chance to examine co-movements between economic series in the time-frequency dimension. It provides more insights about potential interdependence at scales other than one or two scales (Ferrer et al., 2016). By doing so, it gives more rigorous results than standard methods, as wavelet analysis yields information in both the time and frequency dimensions by utilizing the spectral bands of time series as a function of time (Aguiar-Conraria, Azevedo, & Soares, 2008). It allows us to distinguish a single occasion truncated in one frequency range and coherent structures across varying scales. Additionally, wavelet analysis employs both nonstationary and locally stationary data (Antonakakis, Chang, Cunado, & Gupta, 2017). For that reason, wavelet analysis has become increasingly popular in economics and finance because of its flexibility (Antonakakis et al., 2017; Ferrer et al., 2016; Yang et al., 2017). A wavelet represents a small "wave packet" that grows and decays in a given period; at the same time, wavelet functions are based on a measure of location, scale parameters, and another wavelet function, ψ in L^2 (R), defined as

$$\psi_{\tau,s}(t)=\frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right)s,\tau\in R,s\neq 0 \tag{1}$$

where s represents the scale parameter, which adjusts for wavelet length; τ stands for the location parameter showing whether the wavelet is centered; $\sqrt{|s|}$ represents a factor of normalization that conserves unit variance of the wavelet; and $|\psi_{\tau,s}|=1$ denotes a scaling factor that controls the breadth of the wavelet, as scale and frequency have an inverse relationship. As a result, a lower scale suggests a compressed wavelet that detects a higher frequency while a higher scale shows a stretched wavelet that captures a lower frequency. This paper uses the Morlet wavelet, which is more popular in finance and economics because it utilizes amplitude and phase (Reboredo et al., 2017). The Morlet wavelet is defined as follows:

$$\psi^m(t)=\frac{1}{4\pi^{1/4}}e^{i\varpi_o t}e^{-t^2/2} \tag{2}$$

where $4\pi^{1/4}$ conserves the energy of wavelet as a unit, ϖ_o represents frequency without a unit and points as the central frequency. One must obtain $\varpi_o=6$, which balances the time and frequency localizations. This number is common in the literature on economic applications (Antonakakis et al., 2017; Ferrer et al., 2016; Reboredo et al., 2017). $e^{-t^2/2}$ denotes the Gaussian envelope, and $e^{i\varpi_o t}$ stands for a complex analytic wavelet.

3.2. Continuous wavelet transform (CWT)

There are two types of analysis in wavelet approaches, such as a continuous wavelet transform (CWT) and a discrete wavelet transform (DWT). However, the CWT is better than the discrete wavelet transform because it offers an easy way to select wavelets that depend on the length of data. Additionally, it can interpret and reveal patterns that carry hidden information easily because of its redundancy (Aguiar-Conraria & Soares, 2011). It is defined as:

$$W_x(s)=\int_{-\infty}^{\infty}x(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t}{s}\right) \tag{3}$$

where * represents the conjugate for the complex number, and s is the scale parameter that identifies whether the wavelet detects higher or lower parts of time series. This confirms consistency when the condition of admissibility is fulfilled.

3.3. Wavelet coherence

Three different approaches can be applied to identify the dependence between two time series in the time and frequency domains: cross-wavelet power, wavelet power spectrum (WPS), and cross-wavelet transform (Reboredo et al., 2017). The WPS measures the variance of a single wavelet, which detects and measures relations between two-time series; cross-wavelet power assesses the covariance of the time series; and the CWT can control the dependencies of frequency and time between two time series. Aguiar-Conraria et al. (2008) define wavelet coherence (WTC) as "the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local correlation (both in frequency and time), between two-time series." Wavelet coherence is expressed as the coefficient of the correlation of time-frequency space. We define wavelet coherence as follows:

$$R_n^2(s)=\frac{\left|S\left(s^{-1}W_n^{XY}(s)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|\cdot S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)} \tag{4}$$

where R^2 represents wavelet coherence and S is a smoothing operator. Interestingly, the value of wavelet coherence ranges from 0 to 1. It is a localized correlation coefficient in time-frequency space and is a useful technique for analyzing co-movements across two time series. Wavelet coherence can be interpreted similarly to the correlation coefficient, suggesting strong dependence when the value is close to 1 and weak dependence when the value is close to 0. Likewise, the WPS explains the variance of a time series and covariance, which captures cross wavelet power between two time series at each scale or frequency. If the variance of a time series becomes large, the wavelet suggests the existence of a sizable power spectrum. The statistical significance of the wavelet coherence coefficient is estimated using a Monte Carlo simulation, though little is known about its theoretical contribution (Torrence & Compo, 1998).

3.4. Phase difference

A phase difference is expressed as the complete cycle of the time series for a function of frequency, giving us information about a delay on or synchronization between the two time series. In addition, it captures the positive and negative associations and lead-lag relations between two time series in time-frequency dimension. According to Torrence and Webster (1999), the wavelet coherence phase difference is defined as follows:

$$\phi_{xy}(s) = \arctan\left(\frac{\Im\left(\left(s^{-1}W_n^{XY}(s)\right)\right)}{\Re\left(\left(s^{-1}W_n^{XY}(s)\right)\right)}\right) \quad (5)$$

where $\Im$ and $\Re$ denote the imaginary and real component parts of the smooth power spectrum respectively. The coherence phase uses arrows, showing the relationship between the two time series: (1) When the arrows point to the right (left), the series show in-phase (out-of-phase), and the correlation coefficient is positive (negative) and (2) when the arrows point down (up) the second (first) variable leads the first (second) variable by a 90° angle. Further, when the phase difference tends toward zero, it suggests that the variables move together at a given time-frequency.

4. Data and descriptive statistics

The data used in this paper consist of daily exchange rates based on the US dollar and stock indices for the BRICS countries (Brazil, Russia, India, China, and South Africa), covering the sample period from January 1, 2006, to December 31, 2016. Using daily data allows us to capture the behavior of different investors in the markets and makes the number of observations large enough, producing reliable results. It is also suitable for detecting the strength and speed of dynamic links in economic series. The stock indexes studied are the Bovespa (Brazil), the Russian Trading System (RTS) (Russia), the Bombay Stock Exchange (BSE), the SENSEX (India), the Shanghai Stock Exchange (SSE) (China), and the Financial Times Stock Exchange/Johannesburg Stock Exchange (FTSE/JSE) (South Africa). The dataset comes from Thomson Reuters DataStream. The exchange rates were calculated based on USD 1 expressed in the real (BRL/USD), ruble (RUB/USD), rupee (INR/USD), renminbi (CNY/USD), and rand (ZAR/USD) respectively. We computed exchange rates and stock returns as the first difference of the logarithm of daily indexes times 100. In other words, the formula for stock returns can be written as follows:

$$R_t = \log\left(P_t/P_{t-1}\right) \times 100 = (\log P_t - \log P_{t-1}) \times 100 \quad (6)$$

where R_t indicates the returns and P represents index levels at time t and $t-1$.

Table 1 reports the descriptive statistics of exchange rates and stock returns of BRICS economies. In stock returns, daily mean scores of all economic series are analogous in magnitude except the returns on the Brazilian stock index. The standard deviations and minimum and maximum values show that Russian stock returns had the highest volatility among the series, while South African returns had the lowest among the selected countries, and the volatility of stock index returns in Brazil, China, and India were similar during the period 2006 to 2016. The average daily exchange rates of all countries exhibited the same patterns, but the Chinese exchange rates showed the lowest mean scores and lowest volatility among

Table 1
Descriptive statistics of exchange rates and stock returns for BRICS economies.

Countries	Brazil	Russia	India	China	S. Africa
Panel A: Stock returns					
Mean (%)	0.0089	0.0120	0.0158	0.0149	0.0156
Min	−5.2532	−8.9713	−5.0344	−4.0199	−3.2922
Max	5.9409	10.9556	6.5292	3.9236	2.9680
Std. Dev. (%)	0.7570	0.9047	0.6220	0.7415	0.5409
Skewness	0.0168	−0.1720	−0.2715	−0.6371	−0.1822
Kurtosis	8.9349	24.9192	12.6060	7.2872	6.7735
JB	4212.25***	57,467.9 ***	11,069.86 ***	2392.09***	1718.65 ***
Panel B: Exchange rates					
Mean (%)	0.0050	0.0112	0.0082	−0.0023	0.0117
Min	−4.0026	−5.5867	−1.4611	−0.4983	−2.7744
Max	3.8734	4.7492	1.9152	0.7895	4.2669
Std. Dev. (%)	0.4192	0.4197	0.2170	0.0515	0.4678
Skewness	0.2714	0.6508	−0.0052	1.3682	0.4035
Kurtosis	13.6835	31.5094	9.1475	31.3004	7.9383
JB	13,684.21***	97,397.88***	4519.284 ***	96,671.35 ***	2994.137 ***
Observations	2870	2870	2870	2870	2870

Statistical significance at $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.
Standard deviations (std. dev.) minimum (min) and maximum (max), and Jarque-Bera (JB).

the selected countries, and the standard deviation and minimum and maximum values of exchange rates in the BRICS countries, except China, had less significant differences. The skewness was positive for Brazilian stock returns and negative for those in the remaining countries, whereas the skewness of the majority of exchange rates was positive except in India. To that effect, the kurtosis statistic specifies that the distribution of both exchange rates and stock returns for BRICS economies had flat tails. Finally, the Jarque-Bera (JB) statistic rejected the null hypothesis, indicating that the data were normally distributed in all series.

5. Empirical results and discussion

We use wavelet analysis to assess the dynamic links between exchange rates and stock returns for BRICS countries because wavelet analysis is a powerful instrument that enables us to identify co-movements between the selected series quickly. It also explains how the series are related to various frequency bands and how such interactions progress concerning time and across different timescales. Specifically, we employ continuous wavelet analysis, which offers greater understanding than the linear association approach about links among external shocks, exchange rates and stock returns, and localized volatility over time and frequency domains simultaneously. Moreover, we use wavelet coherence to examine co-movement and the lead-lag relationships between exchange rates and stock returns of the BRICS economies. The wavelet coherence and phasing difference show cause-effect relationships between the selected indexes.

5.1. Empirical evidence from continuous wavelet analysis

In this paper, we used the continuous wavelet method to decompose the data into eight levels (2^n, $n = 1, 2, 3, \ldots$) covering different holding periods, namely, short-, medium-, and long-term investment horizons. The horizontal axis represents the time component, and the vertical axis is the frequency component. The horizontal axis covers study periods from 2006 to 2016, corresponding to 500 and 2500 (i.e., 12/2008, 11/2010, 11/2012, 10/2014, and 10/2016), whereas the frequency bands on the vertical axis are based on daily units ranging from 4- to 512-day scales. We further divide these levels into three holding periods, such as the 2- to 64-day scales, which relate to the short term, 64- to 128-day scales, which are associated with the medium term, and 128- to 512-day scales, which are linked with long-term dynamics.

We report the results of the continuous wavelet transform (CWT) in Fig. 1 and Table 2, indicating that exchange rates and stock returns of BRICS countries exhibit significant volatility at the 5% significance level. The CWT is the absolute square value, which measures the variance of economic series, capturing both time and frequency components (Dewandaru, Masih, & Masih, 2017). In Fig. 1, blue and red regions represent low- and high-intensity levels, regions in red show strong variation or high-intensity movements between the series at low (high) frequency bands, and regions in blue indicate weak variation or low intensity. The intensity levels gradually increase from blue to red; the red region shows that the co-movements of exchange rates and stock returns to the shocks in BRICS countries are very high; in contrast, blue regions indicate that co-movements between exchange rates and stock returns to external shocks, such as the global financial crisis in 2008, are low. A black contour indicates a 5% significant level based on the estimation of Monte Carlo simulations with randomized surrogate time series. In addition, a solid curved line, representing the cone of influence (COI), shows the zone affected by edge effects,[1] and blue beyond the COI signifies that interdependence between the series at different time-frequency domains is insignificant (Torrence & Compo, 1998).

According to Fig. 1 and Table 2, stock returns of BRICS economies show an evolution of variances, suggesting strong volatilities at high (low) frequency bands over the period 2006 to 2016. In the Brazilian stock index, returns indicate significant high variation at 2—64 days in 2009 and 2014; 64—128 days around 2009, and 128- to 512-day scales from 2008 to 2010, covering the global financial crisis in 2008, the European debt crisis, and Russian financial turbulence in December 2014. Returns on the Russian stock index show patterns similar to those on the Brazilian stock market, indicating significant variances in the 2-64- and 64—128-day scales in 2009, and 128—512-day scales from 2008 to 2011. Surprisingly, the Russian financial crisis in December 2014 affected Russian stock returns only slightly at 64—128-day scales in 2015. Stock indices in China and South Africa demonstrate significant variation and structural changes over the short (2—64 days), medium (64—128 days), and long term (128—512 days) during the period 2008—2009. Nonetheless, returns on the South African stock market reveal a slight variation in the 128—512-day scales in 2008—2009. Chinese stock returns experienced strong volatility in 2—64-day, 64—128-day, and 128—512-day scales in 2015. Therefore, these results show that stock returns in BRICS countries were highly volatile at low-frequency bands from 2008 to 2010 and from 2015 to 2016, implying that the global financial crisis, European debt crisis, and Russian financial crisis had substantial impacts on stock indexes in the BRICS countries.

By contrast, exchange rates show less volatility in 2—64-day scales: blue is scattered across the majority of the areas and all frequency bands, namely the short, medium, and long term, suggesting a 5% significance level statistically. Orange areas for the long term indicate strong variation but statistical insignificance for exchange rates in the BRICS countries. Nevertheless, exchange rates displayed high variation in 128—512-day scales from 2008 to 2009 in Brazil and from 2014 to 2015 in Russia, while the exchange rate in South Africa showed strong volatility at 64-128- and 128—512-day scales in 2008. Interestingly, the exchange rate in India and China was stable or less volatile for all

[1] For more details, see Grinsted et al. (2004).

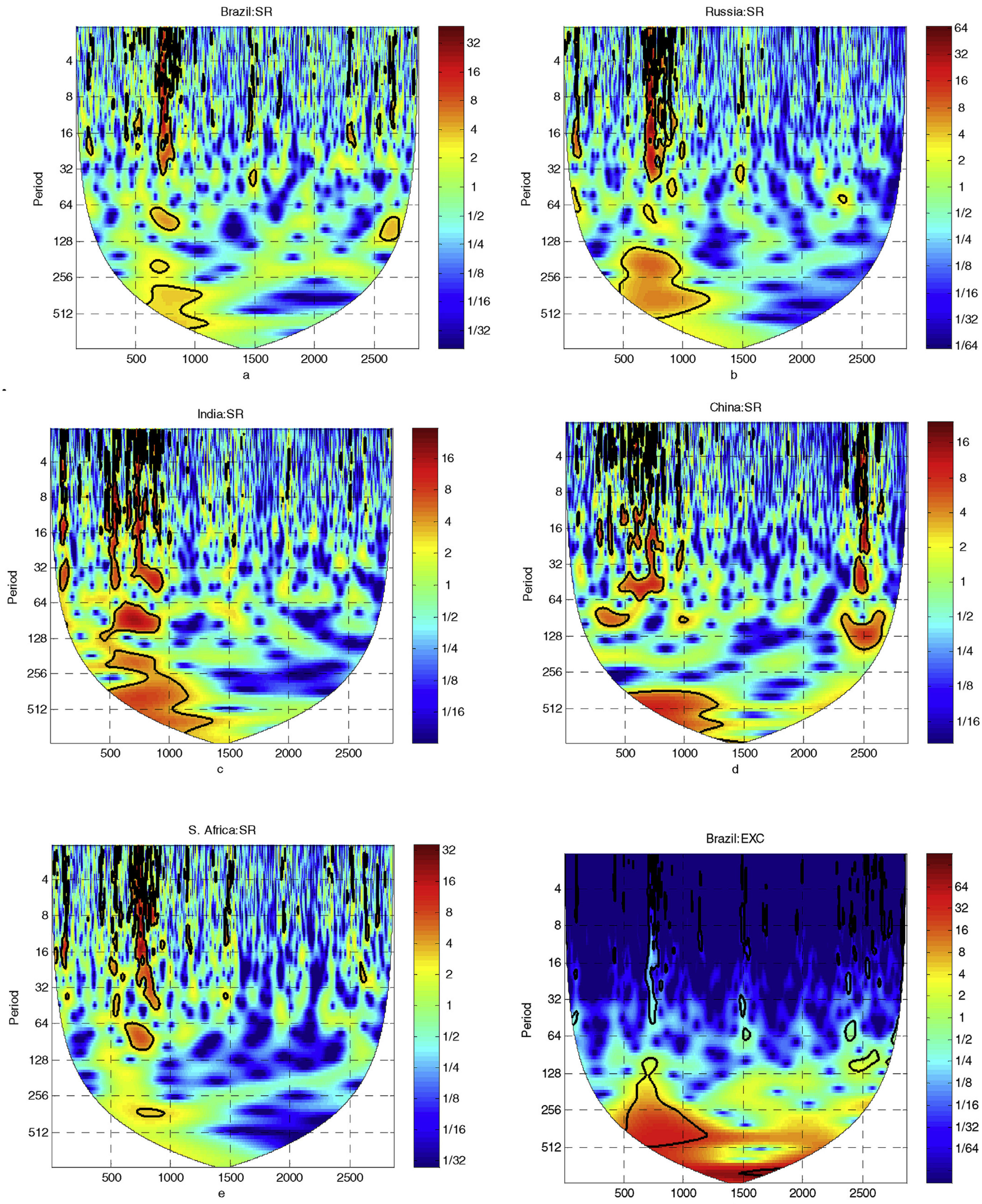


Fig. 1. The continuous wavelet power spectrum of exchange rates and stock returns in the BRICS countries. Notes: The vertical axis is the frequency component while the horizontal axis is the time component; the thick black contour represents a significant region at the 5% level, and the curved black line denotes a cone of influence, which indicates regions affected by edge effects.

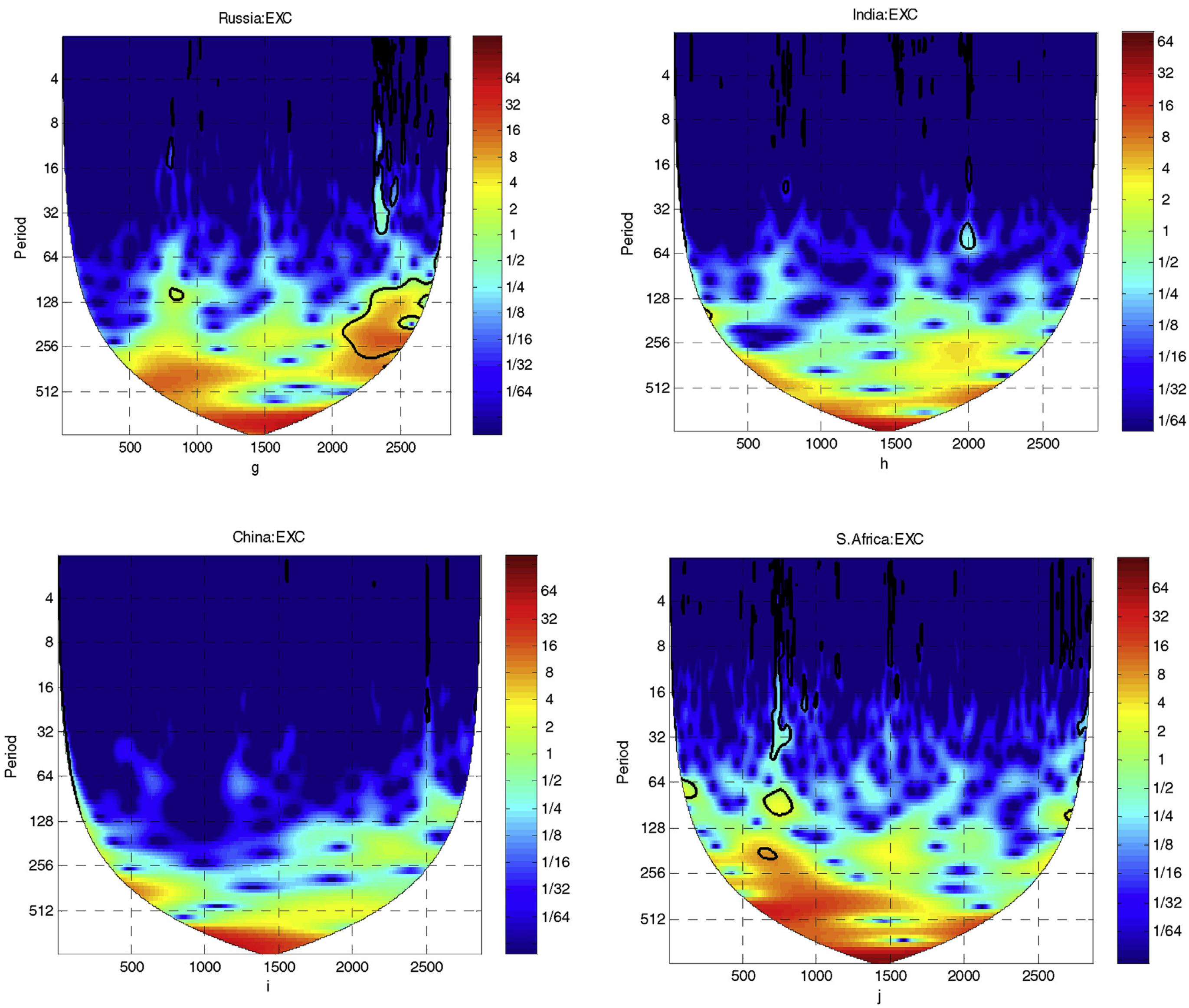


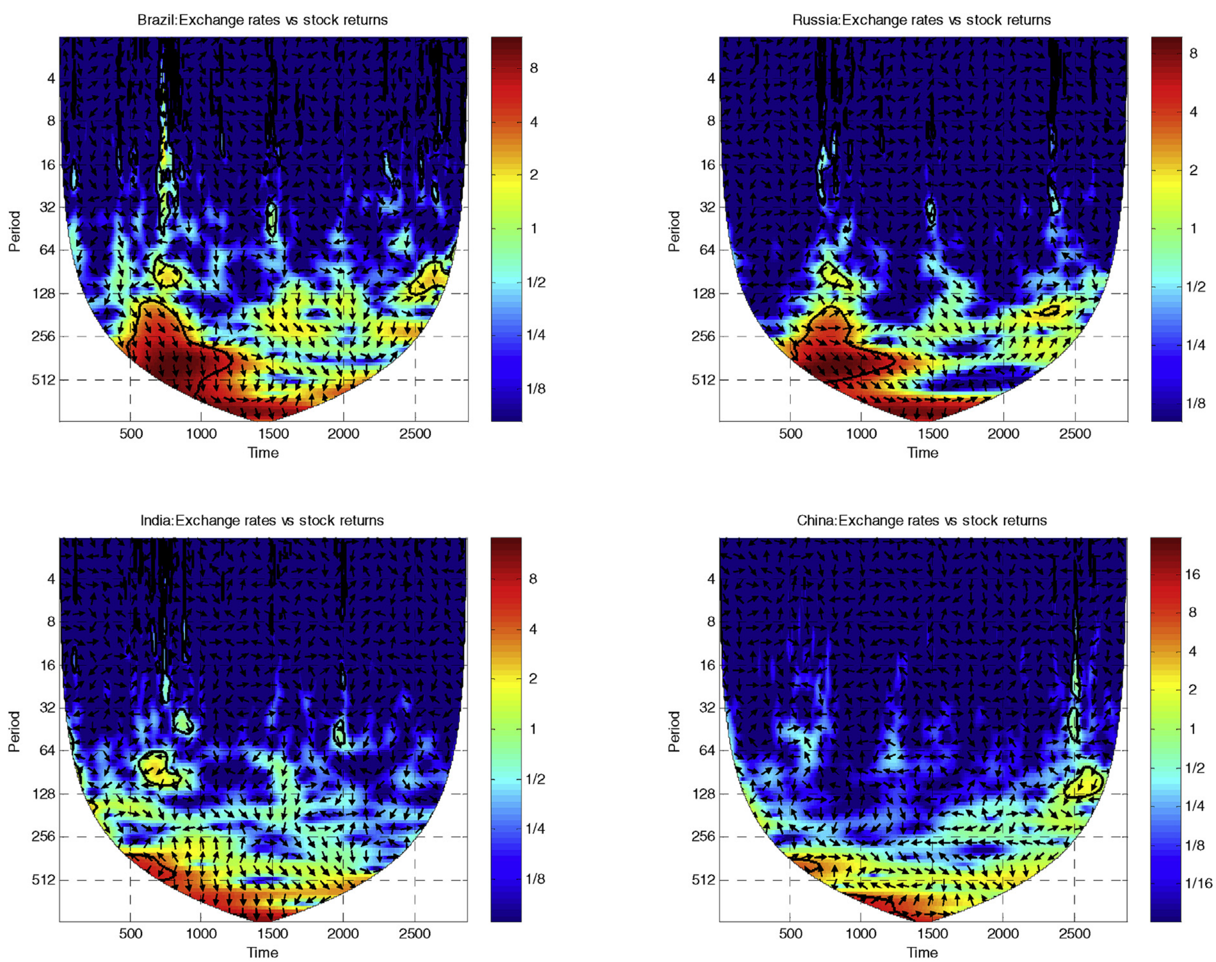
Fig. 1. (*continued*).

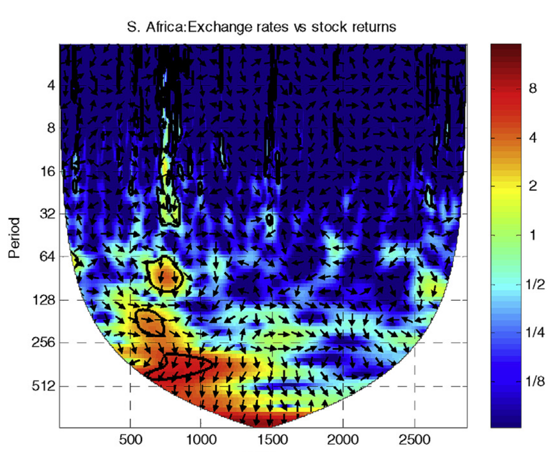
scales during the period from 2006 to 2016. These results were attributed to the fact that exchange rates have limited latitude because they are pegged to the dollar and the euro. With regard to the long term, external shocks affected exchange rates at low-frequency bands in 2008. Thus, we conclude that the exchange rates cluster at low frequencies for the BRICS economies, except for China and India, during the sample period from 2006 to 2016.

Table 2
The results of wavelet power spectrum for exchange rates and stock returns in the BRICS countries.

Days	Scale	Brazil	Russia	India	China	S. Africa
Panel A: Stock returns						
2–64	Short term	2009	2009	2007–2008	2006–2008	2007–2008
		2014			2015	
64–128	Medium term	2009	2008	2007–2008	2007–2008	2007–2008
			2015		2015	
128–512	Long term	2007–2009	2007–2009	2007–2008	2007–2008	2007–2008
				2008–2010	2015	
Panel B: Exchange rates						
2–64	Short term					
64–128	Medium term					2008
128–512	Long term	2007–2009	2014–2015			2008

Fig. 2 presents a CWT that is analogous to the continuous wavelet transform power spectrum plots in Fig. 1, the black contour indicates the 5% significance level, as calculated from Monte Carlo simulations employing phase-randomized surrogate series. The thin black curved line, known as the cone of influence, shows the area affected by edge effects. The CWT reflects the local covariance between exchange rates and stock returns at different scales and time periods. The red (blue) colors indicate high (low) power, the red (warmer) colors imply that the two series have high joint power, whereas the blue (cooler) colors imply that exchange rates and stock returns have lower power. The CWT shows that the relationship between exchange rates and stock returns is significant at low frequency (high scales), suggesting that the two series





500	1,000	1,500	2,000	2,500
12/2008	11/2010	11/2012	10/2014	10/2016

Fig. 2. Cross-wavelet transforms for exchange rates and stock returns in BRICS countries. The vertical axis represents the frequency component, while horizontal axis represents the time component, the thick black contour represents a significant region at the 5% level, and the curved black line denotes a cone of influence, which indicates regions affected by edge effects. Right up and down shows in-phase, while left up and down represents out of phase.

have similar volatility in the long term, except in India and China. In other words, strong covariance is shown in 128–512-day scales around 2008–2010 and 2010–2013. Therefore, the results indicate that the volatility of indexes in BRICS countries experienced fundamental changes only during the sample periods, which means that the BRICS economies are exposed to long-term volatility. Moreover, phase differences demonstrate that the interdependence between exchange rates and stock returns was not homogeneous across time and scales, as shown by arrows that point up, down, right, and left across different times and scales.

5.2. Wavelet coherence

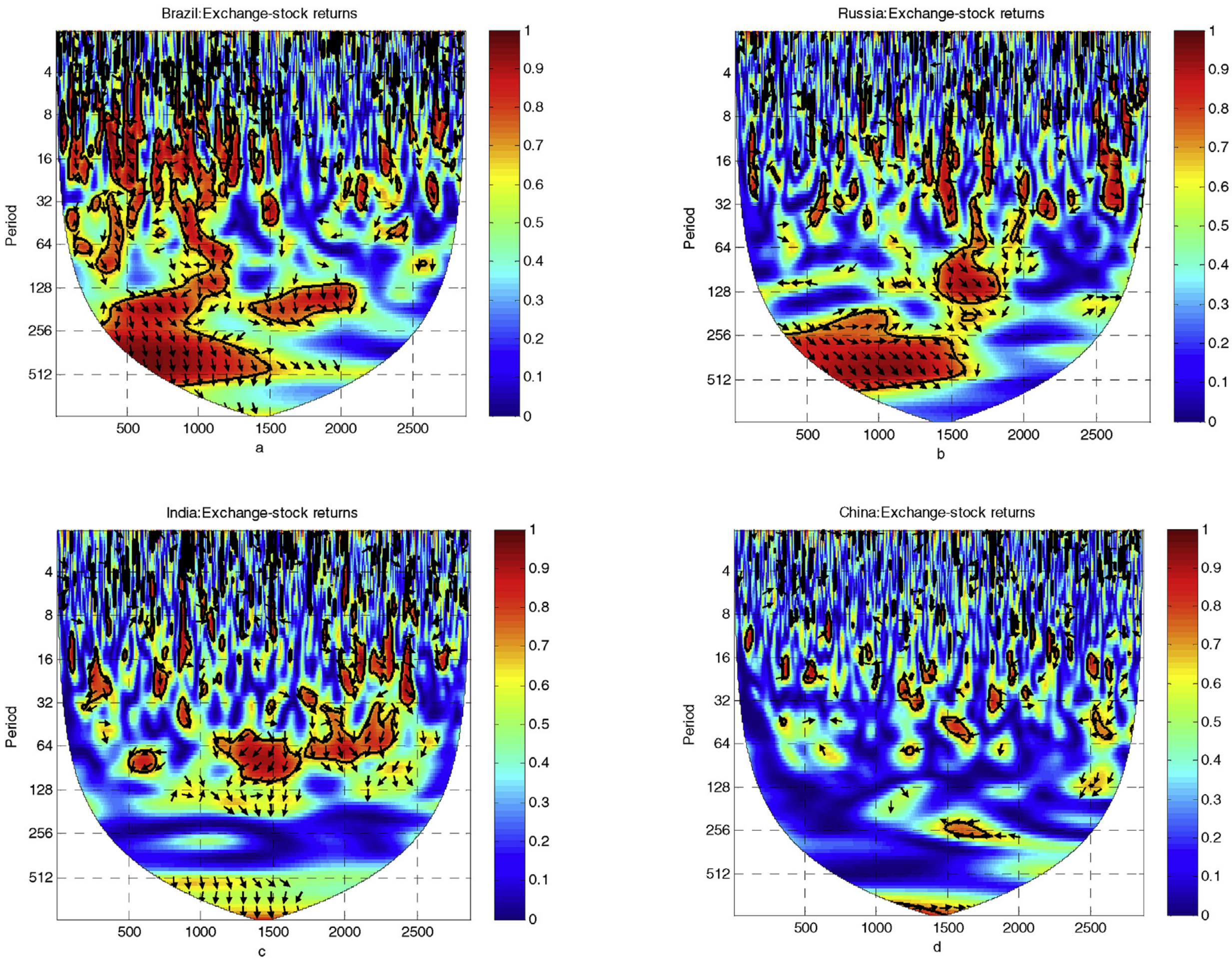
In this section, we investigate the co-movements and lead-lag relationships between exchange rates and stock returns in BRICS countries using the pairwise plots of wavelet coherence. Plots of wavelet coherence are similar to those of continuous WPS and CWT, shown in Figs. 1 and 2. The horizontal axis represents the time element while vertical axis denotes the frequency component, which is transformed to days, and a color code measures the degree of co-movement between the pair of indexes. The warmer (red color) regions indicate that the two series are highly dependent, while cooler (blue color) regions show that the two series are less dependent. The thick black contour in the plots designates the area that is statistically significant at the 5% level, as estimated from a Monte Carlo simulation. Moreover, the wavelet coherence clearly shows zones over time and scales in which every pair of indexes is greatly dependent or otherwise, corresponding to the local correlation ranging from 0.4 to 1. The local correlation of 0.4 designates that the co-movements between the two variables are weak, and the local correlation of 1 shows the existence of strong co-movements. More importantly, using phase differences, wavelet coherence has consistent results on the causality of the series, in which the continuous WPS and CWT reveal structural changes and volatilities, such as booms and busts in the indexes of the BRICS countries in the sample period. However, the results of wavelet coherence need to be interpreted with caution (Dewandaru et al., 2016): they are accentuated at the beginning and end of time periods, which should be interpreted carefully, while the vicinity of a specific point is used in a CWT.

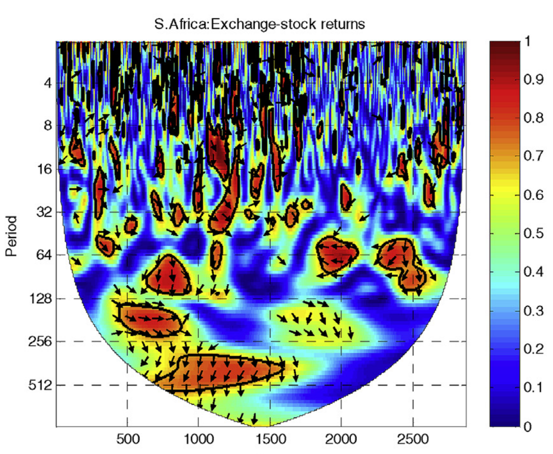
Wavelet coherence thus tends to reveal co-movements in index pairs of BRICS countries, whereas wavelet phase difference determines the dynamic links of indexes by observing lead-lag relationship through different investment horizons. Arrows representing phase differences demonstrate the direction of interdependence and cause-effect associations. Notably, arrows are assumed to measure the wavelet phase difference (Grinsted et al., 2004). Right and left arrows show that the paired series are in-phase and out of phase respectively. A phase difference of zero suggests that the stock return and exchange rates move jointly in the same direction, while an out-of-phase wavelet phase difference indicates that pair series (i.e., exchange rates and stock return) move in opposite directions over specific time and frequency bands. In addition, an in-phase wavelet phase difference suggests a positive relationship; however, an out-of-phase wavelet phase difference indicates a negative association. The right-up or left-down arrows show that stock returns, as the dependent variable, are leading, and the right and down and left and up arrows demonstrate that exchange rates, as an independent variable, are leading.

The plots pair of wavelet coherence reveals that exchange rates and stock returns show significant co-movement over time and frequency domains in the BRICS economies. However, the coherence in the index pair (i.e., exchange rates and stock returns) increases at lower frequency bands (64–128 days and 128–512 days), and they persist from about 2006 to 2016. Co-movements of exchange rates and stock markets demonstrate high coherence in Brazil, Russia, India, and South Africa, but in China, the index pair is statistically insignificant. The correlation between Brazilian exchange rates and stock returns shows that significant interdependence exists at all scales—namely, the short, medium, and long term over 2006–2016; however, the highest level of coherence (co-movement) was recorded at scales ranging from 64- to 512-day scales from 2008 to 2014. These results are ascribed to the global financial crisis around mid-2008, the European debt crisis in 2010, and the Russian financial crisis in December 2014. Moreover, we observe downward right arrows, implying that the causality relationship between exchange rates and stock returns is positive, and, in this case, exchange rates lead stock returns in Brazil. Furthermore, these empirical findings are consistent with those obtained by cross-wavelet power. They also support the stock-oriented theory, which theorizes a positive relationship when demand for financial assets, such as stocks and bonds, increases, and the exchange rate responds to the demand and supply of domestic and foreign financial assets, which are needed to diversify the portfolio internationally (Chkili & Nguyen, 2014).

According to Fig. 3, we find co-movements between Russian exchange rates and stock returns, which suggest a strong relationship; there are two significant regions with high wavelet coherence in 64–128-day and 256–512-day scales, corresponding to the periods 2012–2013 and 2007–2012 respectively. These results were influenced by several episodes, such as the subprime crisis in 2007, the global financial crisis in 2008, and the European debt crisis in 2010. In the significant areas, it is noteworthy to display phase-related information, as shown by arrows. In Russia, the arrows point rightward and downward, implying that exchange rates and stock returns are positively correlated, and exchange rates lead stock returns. These findings confirm the theoretical prediction. In Russia, stock returns are directly sensitive to the appreciation (depreciation) in exchange rates during the sample periods.

In India and South Africa, wavelet coherence, exchange rates, and stock returns are correlated at all times and across low, middle, and high frequencies. Notably, Indian stock market returns are strongly correlated with exchange rates and persist throughout the sample period, and the arrows point





500	1,000	1,500	2,000	2,500
12/2008	11/2010	11/2012	10/2014	10/2016

Fig. 3. Wavelet coherence in exchange rates and stock returns. The vertical axis is the frequency component, while the horizontal axis is the time component; the thick black contour represents significant regions at the 5% level, and the curved black line denotes a cone of influence, which indicates the regions affected by edge effects. Right up and down show in-phase, while left up and down represent out of phase.

leftward and downward in one significant region in 64−128-day scales over the periods 2008, 2010−2012, and 2012−2015, indicating a negative association and that stock returns lead exchange rates. The negative relationship between the index pair is attributed to lower exports. However, South African stock returns are strongly influenced by exchange rates at all frequency ranges. We discover that wavelet coherence increases at different frequency bands, specifically the medium term at 64−128-day scales in 2009, 2013−2014, and 2015−2016 as well as the long term at 128−256-day scales in 2007−2009 and 256−512-day scales from 2009 to 2012. The fluctuations in exchange rates affected stock returns and increased at lower frequency bands, which can be ascribed to the US subprime crisis, the global financial crisis, the

European debt crisis, and Russian financial turmoil. The arrows (lead-lag relationships) point rightward and downward at 128−256 days from 2007 to 2009 and leftward and downward at 64−128 days in 2008, 2014, 2015−2016, and 2009−2012. Therefore, the first suggests a positive relationship between the index pair, and exchange rates lead stock returns, while the latter indicates that stock returns lead exchange rates in the medium term. Additionally, the lead-lag relationships seem to reveal more bidirectional causality at different scales because the arrows point both upward and downward.

However, the wavelet coherence of Chinese exchange rates and stock returns show a weak association, implying no co-movement. There are significant small regions at both the middle and low scales, but these show that wavelet coherence decreases gradually from higher to lower frequency bands until their correlation drops at lower frequency bands. The lead-lag relationships seem to suggest negative associations and that exchange rates lead the stock returns. However, the co-movements between exchange rates and market stock prices are not statistically significant, as the cooler color dominates the area. These findings indicate that stock returns are not sensitive to exchange rates because the Chinese stock markets are well capitalized. They seem to be consistent with previous research (Cai, Tian, Yuan, & Hamori, 2017).

6. Conclusion and implications

We examine the dynamic relationship between exchange rates and stock returns using wavelet analysis, which captures time and frequency components. The wavelet analysis approach has advantages over other estimators, as it allows us to investigate co-movement, volatility, and lead-lag relationships for different investment horizons. We use daily data for the period January 1, 2006, to December 31, 2016, and a sample of countries comprising Brazil, Russia, India, China, and South Africa (BRICS).

Our empirical results reveal that, for the stock returns of BRICS countries, variances concentrate at low frequencies, suggesting strong volatilities at low-frequency bands, while exchange rates are less volatile in the periods 2008−2010 and 2015−2016. Moreover, the wavelet coherences show high co-movements of exchange rates and stock markets in the BRICS countries at the medium and long term, except in China, implying greater correlations, which suggests the existence of strong interdependence between exchange rates and stock returns. Nevertheless, the coherence increases in low-frequency bands and the highest coherence was recorded at scales ranging from 64- to 512-day scales in the period from 2008 to 2014. These results are attributed to several crises, such as global financial crisis in 2008, the European debt crisis in 2010, and the Russian financial crisis in December 2014.

Finally, the lead-lag relationships (phase difference) between exchange rates and stock returns in the BRICS countries have mixed results. In Brazil and Russia, the results suggest that relationships between exchange rates and stock returns are positive at medium- and long-term scales, implying that exchange rates lead stock prices, and therefore these findings are consistent with stock-oriented theory. In India, the index pair shows a negative association and stock returns lead exchange rates in 64−128-day scales over the periods 2008, 2010−2012, and 2012−2015; these results are consistent with flow-oriented theory. Moreover, South African stock returns are strongly influenced by exchange rates in both directions, indicating that the lead-lag relationships thus seem to reveal a bidirectional causality at different scales, specifically, medium- and low-frequency bands of scales over the period 2006 to 2016. Interestingly, the wavelet coherence of Chinese exchange rates and stock returns indicate weak associations, implying no co-movements. These results show that the Chinese stock market is not sensitive to exchange rates because they are well capitalized.

These findings have implications for investors, as they are heterogeneous in their investment horizons, rather than having similar holding periods. For instance, short-term investors can use stock returns as a hedging instrument because of their weak correlation with exchange rates, whereas investors with medium- and long-term investment horizons suffer losses arising from strong coherence in middle- and low-frequency bands that decrease the diversification benefits of underlined assets. Thus, investors, as well as portfolio managers, should take into account the varying frequency bands of exchange rates and stock returns, which have comprehensive co-movement between the series and aid them in making correct and precise decisions. Additionally, the study suggests that policymakers make an effort to understand lead-lag relationships so that they can develop sound policy measures to prevent financial risk.

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