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THE DYNAMIC RELATIONSHIPS BETWEEN THE BALTIC DRY INDEX AND THE BRICS STOCK MARKETS: A WAVELET ANALYSIS

Pao-Lan Kuo[1+]
Chien-Liang Chiu[2]
Chan-Sheng Chen[3]
Mei-Chih Wang[4]

[1,2]*Department of Banking and Finance, Tamkang University, New Taipei City, Taiwan (R.O.C.).*
[1]*Email: iampaulinekuo@gmail.com Tel+886-910-653-288*
[2]*Email: 100730@mail.tku.edu.tw Tel: +886-2-2621-5656 Ext. 2854*
[3]*Department of Banking and Finance, Tamkang University, Former President, Central Deposit Insurance Corp., Taiwan (R.O.C.).*
[3]*Email: johnson.c1002@gmail.com Tel: +886-2-2621-5656 Ext. 2854*
[4]*Providence University Finance, Shalu Dist., Taichung City, Taiwan (R.O.C.).*
[4]*Email: wangsona@gmail.com Tel: +886-910-653-288*

(+ Corresponding author)

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ABSTRACT

This paper studies the dynamic relationships between the Baltic Dry Index (BDI) and the BRICS stock markets by wavelet analysis for the period from January 1996 to March 2019. Compared to the causality based on linearity and the choosing of the period of lags, as well as given the significant evidence of nonlinearity, we used wavelet analysis to analyze the dynamic relationships between the two series in both time and frequency domains, which helped us to demonstrate the causality across different horizons. Due to wavelet analysis, we found that the BDI and the Brazilian stock market had a significantly positive relationship from 2002 to 2011 in the medium term and that the Brazilian stock market led the BDI from 2002 to 2004 and from 2009 to 2011. The wavelet analysis showed that the Russian and Indian stock markets dominated the BDI from 2005 to 2016 in the long term and from 2002 to 2011 in the medium term, respectively. The South African stock market and the BDI had a medium term, positive, and co-movement relationships. The empirical results of Brazil and South African indicated that commodity import- and export- related countries have similar interactions. Lastly, wavelet analysis revealed that the BDI lead the Chinese stock market from 1996 to 1998 in the medium term, while the Chinese stock market turned to dominate the BDI from 2001 to 2011, both in the medium and long term.

Contribution/ Originality: This study used new estimation methodology of a wavelet-based approach to analyze the dynamic relationship between BDI and BRICS stock markets in time and frequency domains, and successfully distinguished the lead-lag relationship between the BDI and the five stock markets, that the conventional methodology could not distinguish.

1. INTRODUCTION

The Baltic Dry Index (hereafter, BDI) is an indicator of transportation costs for various dry bulk cargoes shipped by sea and has been listed on the Baltic Exchange in London since May 1985. Some previous research has focused on the BDI, freight rates and the shipping industry (described below). Stopford (2005); Stopford. (2009) detailed the Trade Development Cycle and Business Cycle as the two main factors that affect the shipping industry, with the Business Cycle as the most important as this points out the nexus between the BDI and business. Thorsen

(2010) found an equilibrium relationship between OECD GDP and the freight rates in dry bulk shipping and confirmed that freight rates (and also the BDI) depend on the global economy (this finding is in line with those of Kavussanos (1996).

Bakshi, Panayotov, and Skoulakis (2011) showed that the BDI growth rate not only demonstrates a positive and significant relationship with emerging market (including the BRICS[1], i.e., Brazil, Russia, India, China, and South Africa) stock returns, but that it also predicts commodity index performance and global economic activity. Erdogan, Tata, Karahasan, and Sengoz (2013) explored the changes in the BDI to help explain the changes in the Dow Jones Industrial Average (DJIA) and determined that the BDI leads the DJIA in the longer term.

Bhar and Hammoudeh (2011) examined the dynamic interrelationships among commodities and commodities-relevant financial variables and pointed out that the interrelationships among them are regime-dependent. Some research has examined the BDI or shipping industry within financial portfolios and shown that they provide the ship-owner with a suboptimal risk-return profile on the market (Cullinane, 1995; Mensi, Hammoudeh, Reboredo, & Nguyen, 2014). To date, research has shown that the importance of the BDI in global economic and global financial markets is obvious.

According to the IMF (International Monetary Fund, 2013) in 2015 the five BRICS countries represented approximately 41% of the world population and as of 2018, these five nations have a combined nominal GDP of 23.2% of the gross world product. Golinelli and Parigi (2014) stated that over the past few years the growth of advanced and emerging (especially the BRICs) economies has been severely divergent, meaning that the tracking of world economic growth can no longer ignore emerging countries. Mensi et al. (2014) and Graham, Peltomäki, and Piljak (2016) suggested that global stock and economic activity has an influence on the BRICS stock markets. In addition, Ahmad, Sehgal, and Bhanumurthy (2013) and Bekiros (2014) found interdependence between global crisis events and BRICS stock markets. This interdependence inspired international investors interested in the co-movements between the BRICS stock markets, global elements, and other financial assets (Apergis & Payne, 2013; Han, Wan, & Xu, 2019; Harvey, 1995).

Based on its economic and world trade status, according to the WTO (World Trade Organization[2]), China is the biggest exporting country in the world. In Brazil, the GDP has grown 12% through import- and export-related activity. Russia is one of the largest grain exporters in the world, and exporting is the main power behind India's economic growth. As mentioned above, the BRICS countries not only depend on international trade but are more important than ever to the world economy, while the BDI has a predictive ability concerning global economic activity. These are the reasons we wanted to investigate the relationship between the BDI and the BRICS equity markets.

In this study, the main goal is to demonstrate the dynamic relationships among the respective BRICS stock markets and the BDI. The first and main contribution of this paper is the use of a wavelet coherency and phase difference both in the time and frequency domains because of the nonlinearity of the BDI and the BRICS stock markets. From a time domain view, the BDI and the BRICS stock markets had a significant positive relationship from 2005 to 2011—covering the period of solid economic performance after the global financial crisis in the emerging markets—whereas the connection disappears after 2011 when the relationship suffered from the European debt crisis, and the economies of the emerging markets diverged. Second, during the significant linkage period, wavelet analysis helped us to distinguish not only the lead-lag relationship but also the frequency and the structural change, while the linear Granger causality, which is subject to the choosing of lag periods and the

[1] Since Dec. 2010, South Africa has entered into BRICs; thus, BRICs expanded from four countries (Brazil, Russia, India, and China) to five countries (Brazil, Russia, India, China, and South Africa).

[2] The website of World Trade Organization is https://www.wto.org/.

assumption of parameter stability in the full-sample period, cannot determine the lead-lag relationship between the BDI and the stock markets of Brazil and South Africa.

The remainder of this paper is structured as follows: Section 2 describes the wavelet methodology; Section 3 presents the data and the corresponding stock market indices, while Section 4 discusses our findings; and Section 5 concludes the paper.

2. METHODOLOGY

We analyzed the dynamic nexus between the BDI and the BRICS stock markets. Wavelets are localized in both time and frequency domains and allow for the analysis of time-frequency dependencies between two time series; this method is more effective for conducting the estimation of spectral characteristics of a time series as a function of time (Aguiar-Conraria, Azevedo, & Soares, 2008). Wavelet analysis has a significant advantage when the underlying series are non-stationary or locally stationary (Roueff & Von Sachs, 2011). Wavelet analysis allows a simultaneous assessment of co-movement and causality between the two returns in both the time and frequency domains (Li, Chang, Miller, Balcilar, & Gupta, 2015). Following Li et al. (2015) we adopted the wavelet squared coherency as follows:

$$R^2_{xy}(\tau,s) = \frac{\left|S(s^{-1}Z_{xy}(\tau,s))\right|^2}{S(s^{-1}|Z_x(\tau,s)|^2)S(s^{-1}\left|Z_y(\tau,s)\right|^2}, \text{ where } R^2_{xy}(\tau,s) \in [0,1] \quad (1)$$

where $Z_{x,y}(\tau, S)$ is the continuous wavelet transform, and $S(\cdot)$ is the smooth operator normalizing time. Zero coherence indicates no co-movement between the BDI and the BRICS stock markets, while the highest coherency implies the strongest co-movement between them. In the empirical section, the squared wavelet coherency is also clearly marked by color bars on the right side of the wavelet coherency plots, with red color corresponding to a strong co-movement, whereas the blue color corresponds to a weak co-movement (shown in Figure 2 to Figure 6).

Following Bloomfield et al. (2004) we estimated the wavelet phase difference between $x(t)$ and $y(t)$ to measure the lead-lag relationship between the two series. The wavelet phase difference was defined as the ratio of the imaginary component $Z_{xy}(\tau, s)$ to the actual component as follows:

$$\emptyset_{xy} = \tan^{-1}\left(\frac{\zeta\left(S(s^{-1}Z_{xy}(x,y))\right)}{\eta\left(S(s^{-1}Z_{xy}(x,y))\right)}\right), \text{ with } \emptyset_{xy} \in [-\Pi,\Pi] \quad (2)$$

Where ζ and η equal the imaginary and real parts of the smoothed cross-wavelet transform, respectively.

A phase difference $\emptyset_{xy}(\tau, s)$ of zero indicates that two underlying series move together, while the phase difference $\emptyset_{xy}(\tau, s) \in (0, \pi/2)$ means the series are in phase (positively co-moved) with $x(t)$ leading $y(t)$. If $\emptyset_{xy}(\tau, s) \in (\pi/2, \pi)$ then the series are out of phase (negatively co-moved) with $y(t)$ leading $x(t)$. If $\emptyset_{xy}(\tau, s) \in (-\pi/2, -\pi)$, then the series are out of phase with $x(t)$ leading $y(t)$. If $\emptyset_{xy}(\tau, s) \in (0, -\pi/2)$, then the series are in phase with $y(t)$ leading $x(t)$. Note that the phase difference can also be indicative of causality between $x(t)$ and $y(t)$ in both the time and frequency domains. Obviously, wavelet analysis, which has a significant advantage when the underlying series are non-stationary or locally stationary (Roueff & Von Sachs, 2011) may reveal proper statistical power more than the conventional Granger causality test, which requests parameter stability in the full-sample period and a single causal-link holding for the whole sample period, as well as at each frequency (Tiwari, Mutascu, & Andries, 2013).

3. DATA AND THE CORRESPONDING MARKET INDICES

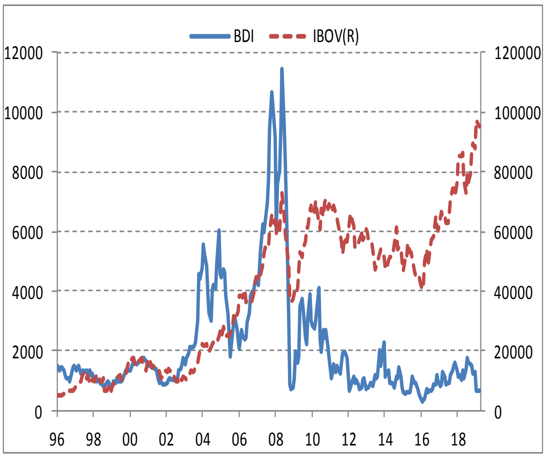
In this paper, we studied the contemporaneous and dominant dynamics between the BDI and the BRICS stock markets. We used BDI, IBVO (Ibovespa Brazil Sao Paulo Stock Exchange Index), RTSI (Russian Trading System Cash Index), SENSEX (India's benchmark index), SCHOMP (Shanghai Stock Exchange Composite Index), TOP40 (Africa Top40 Tradeable Index) to represent the Baltic Dry Index and the Brazilian, Russian, Indian, Chinese, and South African stock market indexes, respectively. Returns were calculated by way of the sequential difference of the natural logarithm of the closing prices of the variables:

$$R_t = \ln({}^{P_t}/_{P_{t-1}}) \times 100$$

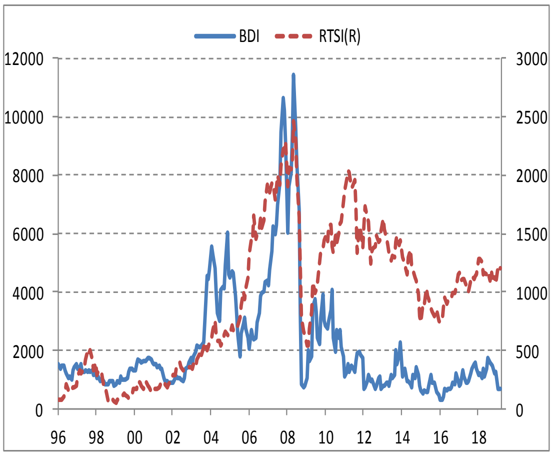
The sample periods of the row data were monthly, covering 1996:1~2019:3 (279 months), and were collected from Bloomberg.

In Figure 1, Panel A to Panel E shows the row data of the pair variables, BDl, and IBVO, RTSI, SENSEX, SCHOMP, TOP40. As shown in Figure 1, the two series were in lockstep from the beginning of the sample period 1996. From 2007 to 2008, during the global financial crisis, the BDI, a leading economic indicator of average global freight rates, crashed from its record high level of 11,793 points (20 May 2008) down to its lowest historic level ever at 290 points (10 February 2016) (Syriopoulos & Bakos, 2019). When the global economy undergoes recession, dry bulk shipping companies go bankrupt; thus, the BRICS stock markets all crashed, and then stock prices explored their own divergent economic conditions.

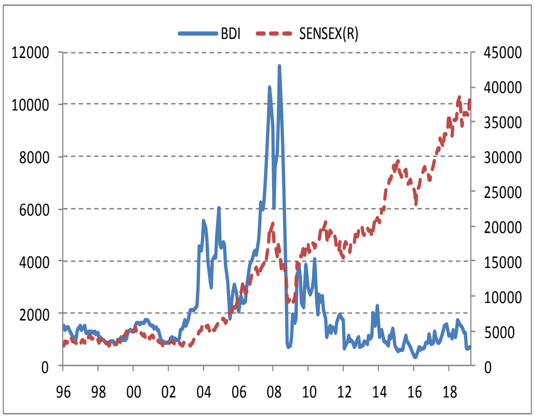
Descriptive statistics and stochastic properties for the rate returns are reported in Table 1. The difference between the standard deviation values showd that Δln (BDI) and Δln (RTSI) were more variable than others. Based on the Jarque-Bera test, the hypothesis of normality of the unconditional distributional for all series were rejected; thus, it was natural to speculate that focusing on causality only in terms of the conditional mean would be improper (Antonakakis, Chang, Cunado, & Gupta, 2018). Then, using the conventional augmented (Dickey & Fuller, 1979) the results in Table 1 indicate that all return series were stationary.



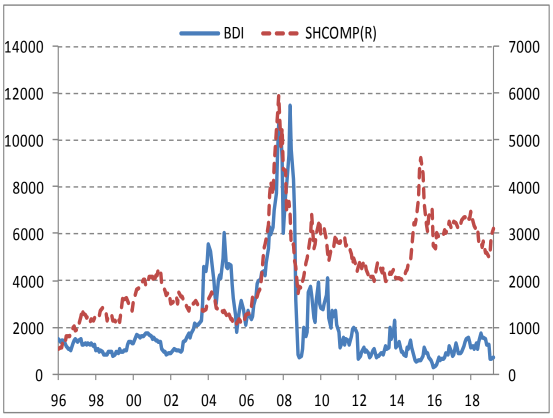
Panel A: BDI and IBOV



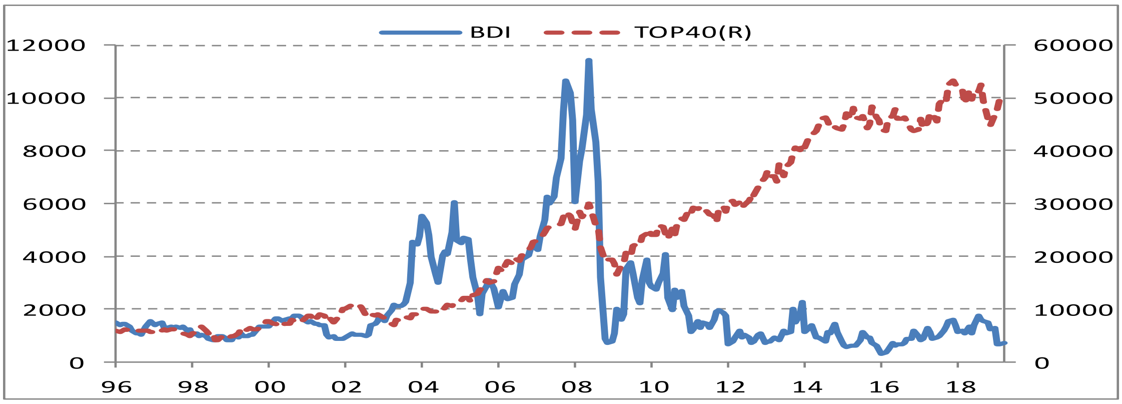
Panel B: BDI and RTSI



Panel C: BDI and SENSEX



Panel D: BDI and SHCOMP



Panel E: BDI and TOP 40

Figure-1. Trend Graph.

Note: This figure deposits the trends of BDI, IBOV, RTSI, SENSEX, SHCOMP, and TOP40. Monthly data from January 1996 to March 2019, with a total of 279 observations used. All the data are obtained from Bloomberg.

Table-1. Descriptive statistics.

	Δln (BDI)	**Δln (IBOV)**	**Δln (RTSI)**	**Δln (SENSEX)**	**Δln (SHCOMP)**	**Δln (TOP40)**
Mean	-0.280659	1.049977	0.970373	0.927881	0.629324	0.772526
Median	1.045200	1.317308	1.309920	1.034893	0.691816	0.956507
Maximum	67.10700	21.54516	44.45920	24.88511	27.8056□	13.76323
Minimum	-133.0000	-50.34140	-82.44950	-27.29919	-28.27834	-33.97558
Standard Deviation	21.55480	8.378180	13.41702	6.827382	7.928857	5.593285
Skewness	-1.210228	-1.185154	-1.115947	-0.361223	-0.199400	-0.948471
Kurtosis	9.747700	8.166079	9.183822	4.072896	4.722888	7.921885
Jarque-Bera	595.2681	374.2197	500.6433	19.37929	36.22554	322.2870
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF(level)	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***

Note: p-value corresponds to the test of normality based on the Jarque-Bera test.

4. EMPIRICAL RESULTS

Following the conventional econometric approach, we conducted the linear Granger causality test based on a vector autoregressive model of order p (VAR(p)) to compare it to the wavelet analysis. The determination of the lag orders was AIC. The results of the linear Granger causality tests are shown in Table 2.

The null hypothesis that the Brazilian stock market rate of return does not Granger cause the BDI rate of return could not be rejected, even at the 10% level of significance; and the null hypothesis that the BDI rate of return does not Granger-cause the Brazilian stock market rate of return could not be rejected at a conventionally significant level, meaning that the Brazilian stock market and the BDI contained no information about each other.

To conclude, we investigated whether the Russian stock market rate of return Granger causes the BDI rate of return, whether the BDI rate of return dominates the Indian stock market rate of return, and whether the Chinese stock market rate of return and the BDI rate of return have bidirectional movement. Also, while the South African stock market and the BDI had no reciprocal causation, this result was the same as the relationship between the Brazilian stock market and the BDI.

Table-2. Linear granger causality test.

Null Hypothesis:	Lags	p-value
Δln (IBOV) ≠>Δln (BDI)	1	0.5701
Δln (BDI) ≠>Δln (IBOV)		0.6462
Δln (RTSI) ≠>Δln (BDI)	4	0.0671**
Δln (BDI) ≠>Δln (RTSI)		0.6580
Δln (SENSEX) ≠>Δln(BDI)	4	0.1245
Δln (BDI) ≠>Δln (SENSEX)		0.0054***
Δln (SHCOMP) ≠>Δln(BDI)	7	0.0292**
Δln (BDI) ≠>Δln (SHCOMP)		0.0817*
Δln (TOP40) ≠>Δ ln(BDI)	1	0.1387
Δln (BDI) ≠> Δln (TOP40)		0.6002

Note:
1.Δln (BDI), Δln (IBOV), Δln (RTSI), Δln (SENSEX), Δln (SHCOMP), Δln (TOP40) represent rate of the return of the Baltic Dry Index, and the rate of returns of stock markets of Brazil, Russia, India, China, and South Africa, respectively.
2. "*","**","***" represent 10%, 5%, and 1% significance levels, respectively.

Next, we examined a nonlinearity test by applying the Broock, Scheinkman, Dechert, and LeBaron (1996) BDS) test. As we see from Table 3, the null of *iid* residuals was strongly rejected for all cases, except for the residual in the AR(4) and VAR(4) model of the Indian stock market rate of return, the residuals of rate of returns of the Indian stock market and the BDI under dimension of 2(Δln (SENSEX) BDS test), the residual in the AR(7) and VAR(7) model of the Chinese stock market rate of return, and the residuals of rate of returns of the Indian stock market and the BDI under dimension of 2(Δln (SHCOMP) BDS test). By applying the Broock et al. (1996) BDS) test, because of the existence of nonlinearity, we found evidence to disclose misspecification of the VAR model; thus, using the conventional linear Granger causality test to examine the lead-lag interaction between two series may be not reliable. This opinion is the same as that of Antonakakis et al. (2018).

Table-3. Broock et al. (1996) BDS test.

Δln (IBOV) BDS test			M		
	2	3	4	5	6
AR(1): Δln (BDI)	0.0084	0.0021	0.0003	0.0000	0.0000
AR(1): Δln (IBOV)	0.0026	0.0004	0.0001	0.0000	0.0000
VAR(1):[Δln (BDI), Δln (IBOV)]	0.0617	0.0317	0.0100	0.0006	0.0001
VAR(1):[Δln (IBOV), Δln (BDI)]	0.0084	0.0009	0.0003	0.0000	0.0000

Δln (RTSI) BDS test			M		
	2	3	4	5	6
AR(4): Δln (BDI)	0.0084	0.0021	0.0003	0.0000	0.0000
AR(4): Δln (RTSI)	0.0000	0.0000	0.0000	0.0000	0.0000
VAR(4):[Δln (BDI), Δln (RTSI)]	0.0868	0.0934	0.0498	0.0034	0.0007
VAR(4):[Δln (RTSI), Δln (BDI)]	0.0000	0.0000	0.0000	0.0000	0.0000

Δln (SENSEX) BDS test			M		
	2	3	4	5	6
AR(4): Δln (BDI)	0.0084	0.0021	0.0003	0.0000	0.0000
AR(4): Δln (SENSEX)	0.7060	0.0365	0.0063	0.0012	0.0001
VAR(4):[Δln (BDI), Δln (SENSEX)]	0.0056	0.0035	0.0008	0.0000	0.0000
VAR(4):[Δln (SENSEX), Δln (BDI)]	0.8261	0.0684	0.0136	0.0016	0.0001

Δln (SHCOMP) BDS test			M		
	2	3	4	5	6
AR(7): Δln (BDI)	0.0084	0.0021	0.0003	0.0000	0.0000
AR(7): Δln (SHCOMP)	0.1370	0.0059	0.0001	0.0000	0.0000
VAR(7):[Δln (BDI), Δln (SHCOMP)]	0.1034	0.0296	0.00106	0.0004	0.0000
VAR(7):[Δln (SHCOMP), Δln (BDS)]	0.0250	0.0212	0.00 15	0.3232	0.2833

Δln (TOP40) BDS test			M		
	2	3	4	5	6
AR(1): Δln (BDI)	0.0084	0.0021	0.0003	0.0000	0.0000
AR(1): Δln (TOP40)	0.0019	0.0000	0.0000	0.0000	0.0000
VAR(1):[Δln (BDI), Δln (TOP40)]	0.0279	0.0102	0.0024	0.0001	0.0000
VAR(1):[Δln (TOP40), Δln (BDI)]	0.0024	0.0000	0.0000	0.0000	0.0000

Note: See note to Table 2; m stands for the number of (embedded) dimension which embed the time series into m-dimensional vectors, by taking each m successive points in the series. Value in cell represents the p-value of the BDS z-statistic with the null of *i.i.d.* residuals.

Lastly, we conducted time-varying wavelet analysis to deal with the disadvantage of linear Granger causality, i.e., the assumption of parameter stability over the full-sample period and needing to determine the lag orders used in a VAR model. The results from the wavelet analysis are shown in Figure 2 to Figure 6.

In comparison to the conventional causality analysis, wavelet coherency and phase difference provided better measure correlation between variables; and they indicated the structural changes from time and frequency domains.

We demonstrated that the BDI and the Brazilian stock market had a significant positive relationship from 2002 to 2011 in the medium term, and that the Brazilian stock market led the BDI from 2002 to 2004 and from 2009 to 2011. From 2002 to 2004, the economy of Brazil was rising from the bottom, while during 2009 to 2011, it was in a period of recovery after the global financial crisis. In addition, a wavelet analysis showed that the Russian and Indian stock markets dominated the BDI in the long term from 2005 to 2016 and in the medium term from 2002 to 2011, covering the down- and up-side periods, respectively. The South African stock market and the BDI had a medium-term positive and a co-movement relationship.

The Brazilian and South African stock markets both had co-movement with the BDI from 2005 to 2009, covering the period of the global financial crisis. This result means that commodity import- and export-related countries have similar interactions. In contrast to the linearity of Granger causality, which is subject to the choosing of lag periods and the assumption of parameter stability in the full-sample period, we could not determine the lead-lag relationship between the BDI and the stock markets of Brazil and South Africa.

Finally, wavelet analysis showed that the BDI led the Chinese stock market from 1996 to 1998 in the medium term, with the Chinese stock market turning to dominate the BDI from 2001—the year of China's entry into the WTO (World Trade Organization)—to 2011—the period of China's prosperity—both in the medium and long terms. Generally, the BDI and the BRICS stock markets had a significant positive linkage for the period of January 2000 to July 2008, largely related to the high-energy demand from the BRICS countries to support their fast economic growth (Mensi et al., 2014).

Overall, while the causality is based on the conditional mean, linearity, and the choosing of the period of lags, wavelet analysis allowed us to analyze the dynamic relationships between the two series in both time and frequency domains, thus helping us to demonstrate the causality across different horizons and even the structure change between the two series.

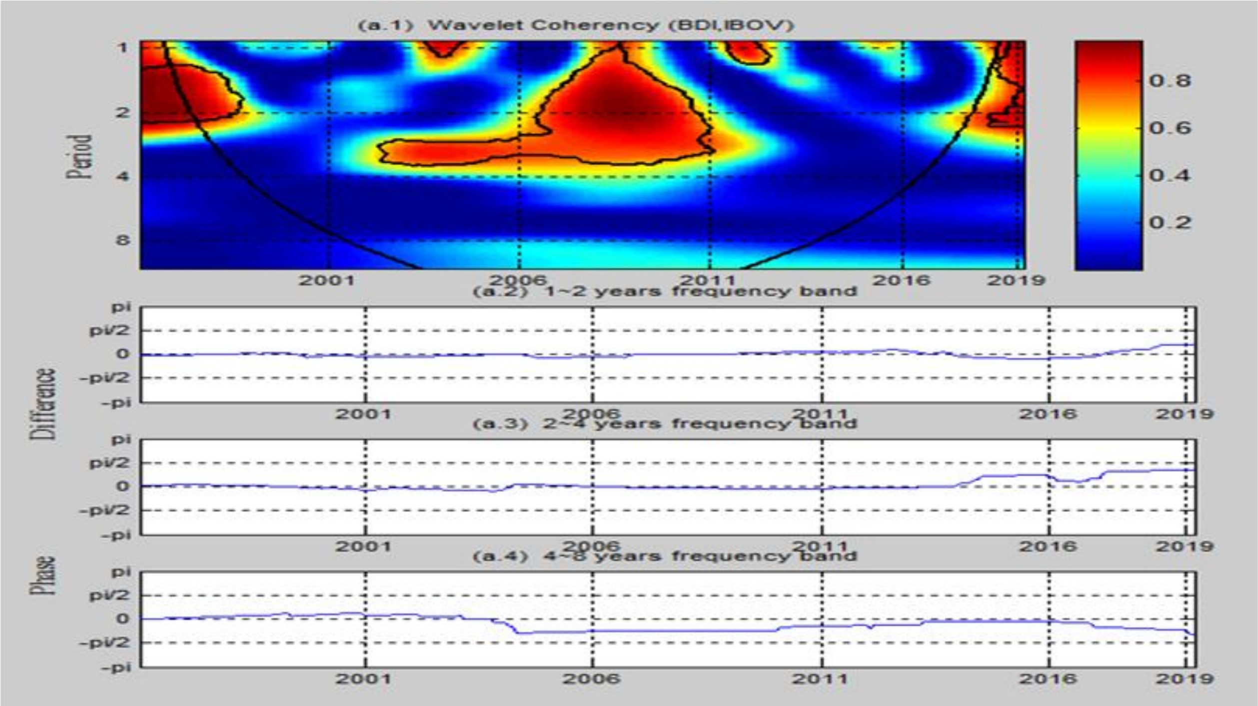


Figure-2. Squared wavelet coherency and phase difference between the Baltic Dry Index (BDI) and the Brazilian stock market (IBOV) from Jan. 1996 to Mar. 2019.

Note: BDI represents the Baltic Dry Index, while IBOV represents the Brazilian stock market. The x-axis refers to time periods. The y-axis is scales (measured in years). The color corresponds to the strength of the correlation.

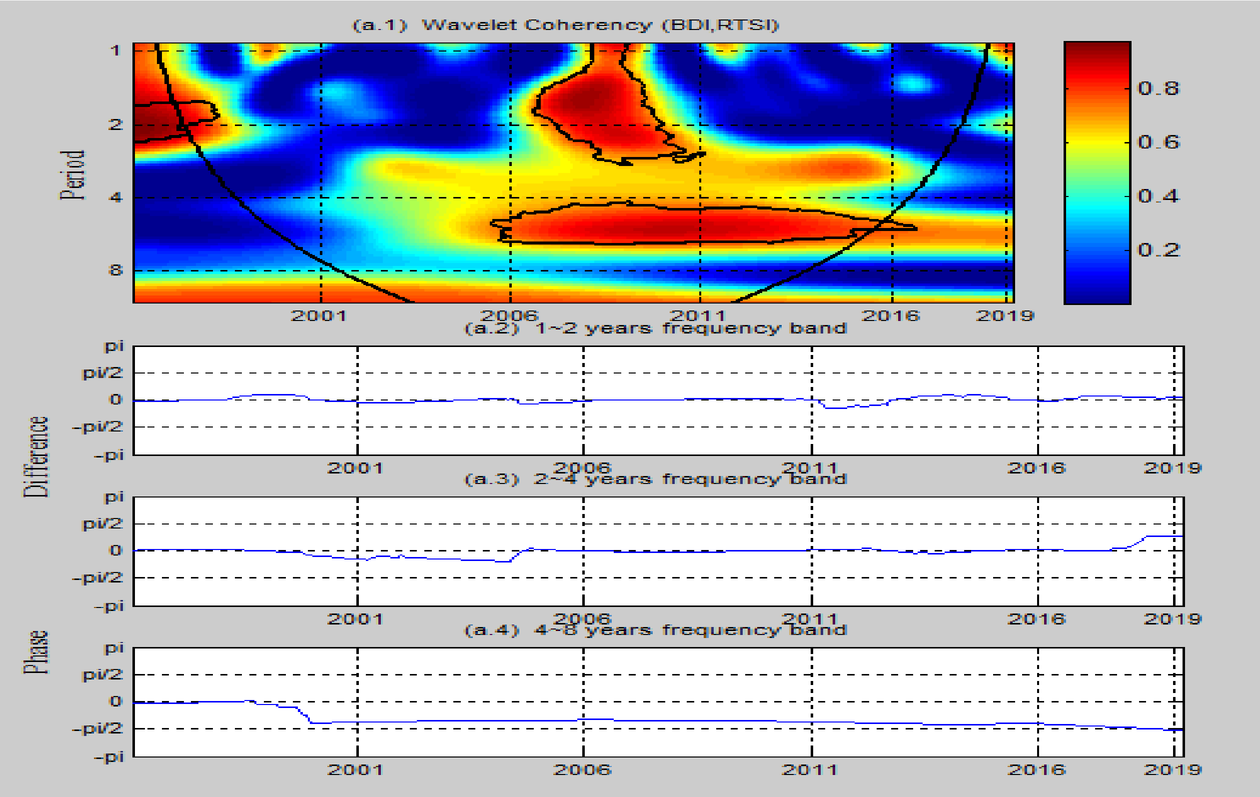


Figure-3. Squared wavelet coherency and phase difference between the Baltic Dry Index (BDI) and the Russian stock market (RTSI) from Jan. 1996 to Mar. 2019.

Note: BDI represents the Baltic Dry Index, while RTSI represents the Indian stock market. The x-axis refers to time periods. The y-axis is scales (measured in years). The color corresponds to the strength of the correlation.

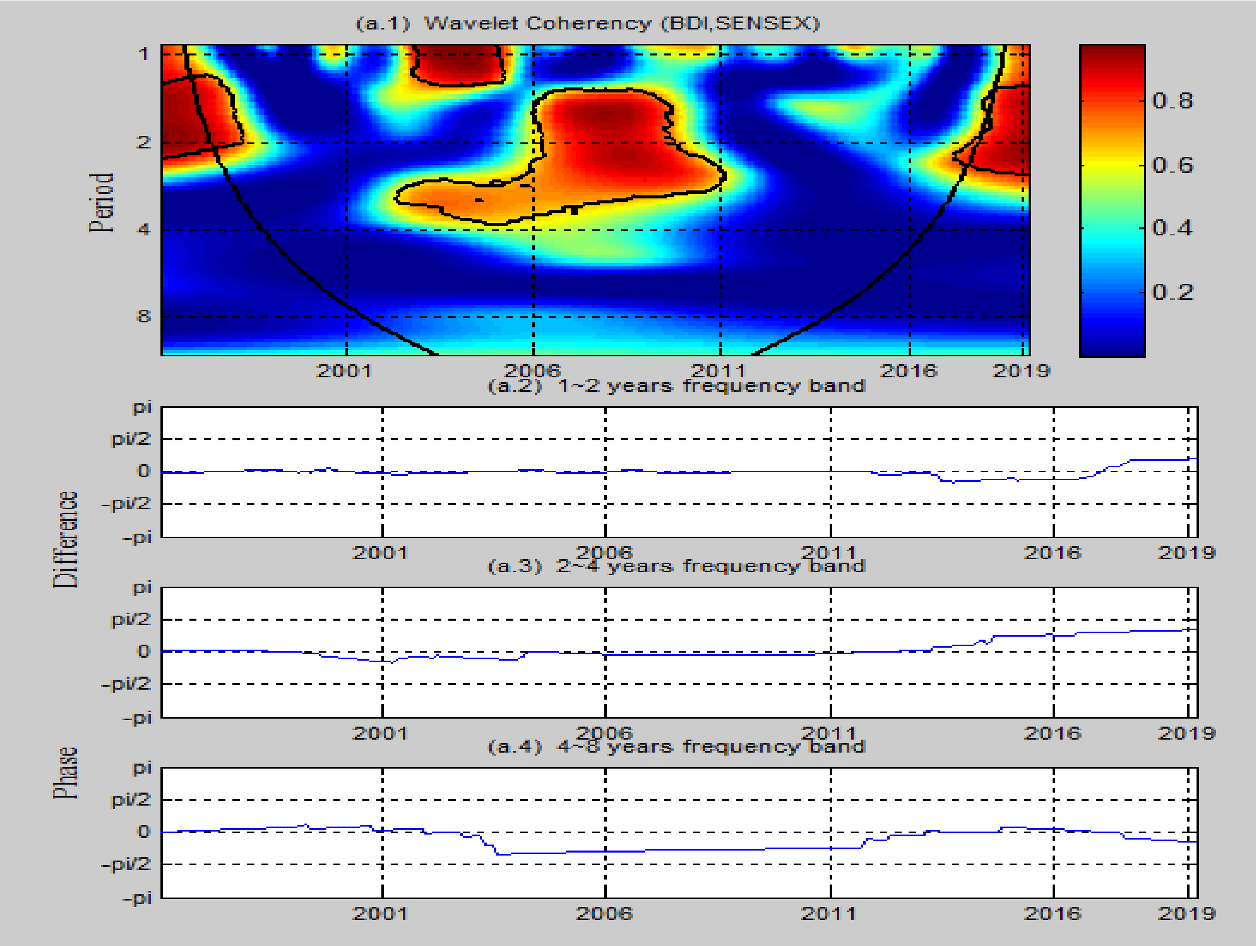


Figure-4. Squared wavelet coherency and phase difference between the Baltic Dry Index (BDI) and the Indian stock market (SENSEX) from Jan. 1996 to Mar. 2019.

Note: BDI represents the Baltic Dry Index, while SENSEX represents the Indian stock market. The x-axis refers to time periods. The y-axis is scales (measured in years). The color corresponds to the strength of the correlation.

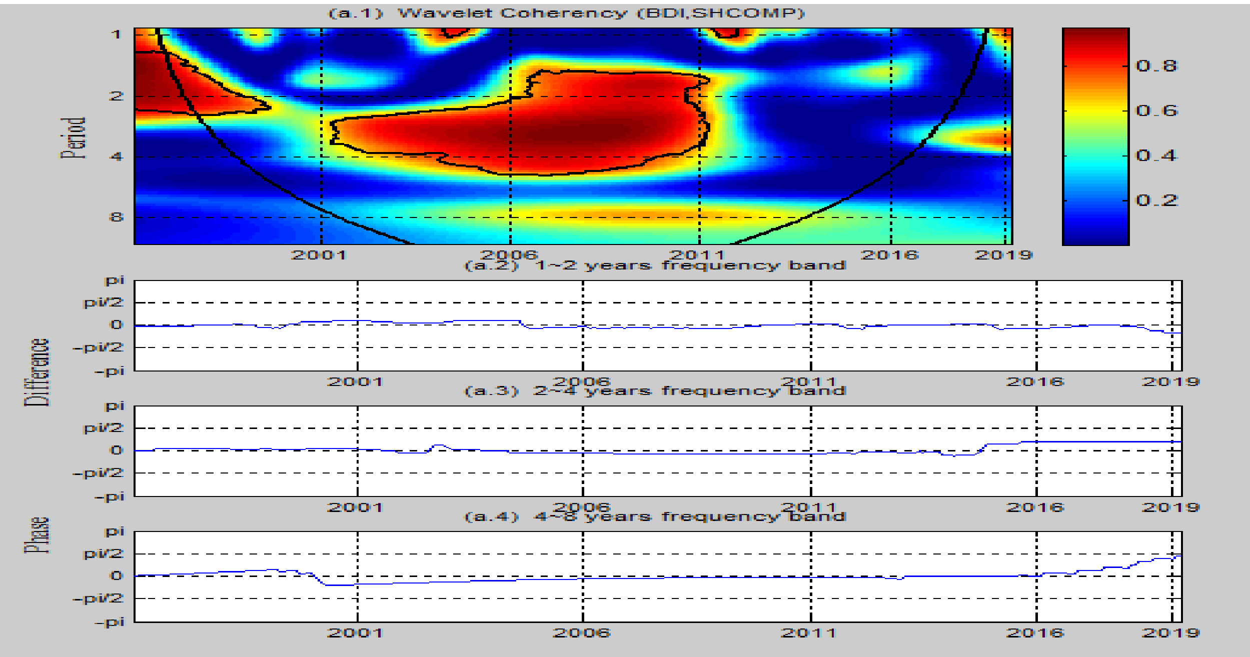


Figure-5. Squared wavelet coherency and phase difference between the Baltic Dry Index (BDI) and the Chinese stock market (SHCOMP) from Jan. 1996 to Mar. 2019.

Note: BDI represents the Baltic Dry Index, while SHCOMP represents the Chinese stock market. The x-axis refers to time periods. The y-axis is scales (measured in years). The color corresponds to the strength of the correlation.

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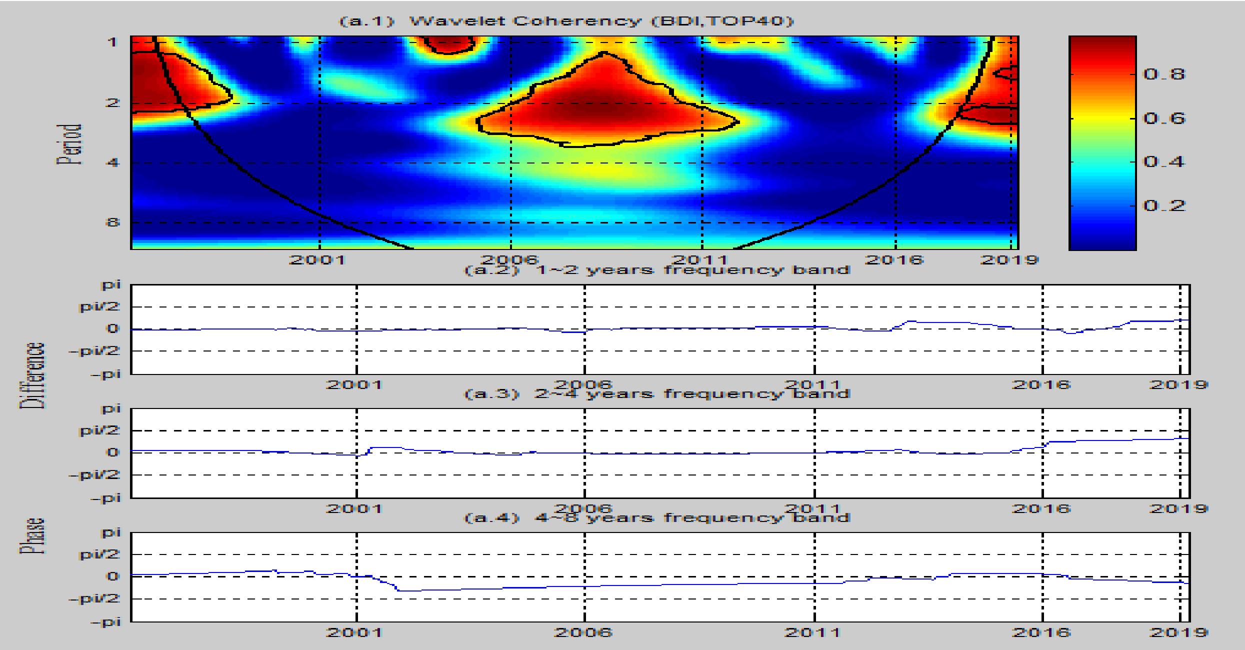

Figure-6. Squared wavelet coherency and phase difference between the Baltic Dry Index (BDI) and the South African stock market (TOP40) from Jan. 1996 to Mar. 2019.

Note: BDI represents the Baltic Dry Index, while TOP40 represents the South African stock market. The x-axis refers to time periods. The y-axis is scales (measured in years). The color corresponds to the strength of the correlation.

5. CONCLUSIONS

Because of the deep linkage between the BDI, global factors, international stock markets, and even the BRICS stock markets, while taking the nonlinearity specification between the BDI and the BRICS stock markets into consideration, we examined the dynamic relationship between the BRICS stock markets and the BDI using wavelet analysis of monthly data covering the sample period from January 1996 to March 2019. A wavelet-based approach helped us to analyze the relationship between these two variables both in time and frequency domains. The latter means that the lead-lag interacts between variables across different horizons, including the short-, medium- and long- terms.

With the conventional methodology, linear Granger causality cannot distinguish the lead-lag relationship between either the BDI and the Brazilian stock market or the BDI and South African stock market. This result may be because the choosing of lag periods constrains the empirical result, requesting parameter stability in the full sample period and a single causal-link holding for the whole sample period, as well as for each frequency (Tiwari et al., 2013).

According to the BDS nonlinearity test, we investigated the nonlinearity between the variables; thus, the use of the linear model may be improper. This was the main reason we turned to the wavelet analysis. Based on the empirical results of the wavelet analysis mentioned above, we plotted some dimensional pictures for the relationship between the BDI and the BRICS stock markets. First, from a time-domain view, the BDI and the BRICS stock markets had a significant positive relationship from 2005 to 2011, covering the period of solid economic performance after the global financial crisis in emerging markets, which was similar to the Chinese stock market in the earlier sample period, 1996 to 1998. Because of Russia's abundant natural resources, the relationship between the Russian stock market and the BDI lasted till 2016. The determination of the structural node is one of the wavelet analysis characteristics.

The connection between the BDI and the BRICS stock markets, except for the Russian stock market, disappeared after 2011 because of the European debt crisis, while the economies of the emerging markets diverged. Second, during the significant linkage period, wavelet analysis helped us not only to distinguish the lead-lag relationship but also the frequency and the structural change, such as the interaction between the BDI and the

Chinese stock market. The BDI led the Chinese stock market in the beginning of the sample period, 1996 to 1998, while the Chinese stock market dominated the BDI from 2001 to 2011. The interaction between the BDI and the Brazilian stock market demonstrated a similar structural change.

In conclusion, while taking the nonlinear and unstable parameter characteristics into consideration, the use of conventional linear methodology to distinguish the co-movement or the lead-lag interaction between two series may be improper. However, by using wavelet analysis as the empirical methodology to examine the lead-lag relationships between variables, we may draw the correct empirical conclusions.

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