9. ASYMMETRIC EFFECTS OF COMMODITY PRICES ON STOCK RETURNS OF THE BRICS COUNTRIES

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Abstract

In today's economic era, as the commodity and stock classes are gradually becoming a part of asset portfolio allocations, it has become notable to observe the liaison among commodity prices and stock returns. The purpose of research in this article is to examine the asymmetric relationship amongst commodity prices and stock returns of BRICS countries over the period 2004M1 to 2020M12. To this aim, the study is using nonlinear Autoregressive Distributed Lag (NARDL) co-integration approach, which considers positive and negative changes in an independent variable. The bound test indicates long run co-integration between all the stock returns and commodity prices. Further, the evidence intends that in the short run, metal and oil prices have significant impact on all the BRICS stock markets but there is no such evidence of short run asymmetric association between gold prices and stock returns. The findings of the study also propose long-run asymmetric association between metal prices, oil prices, gold prices and stock returns of all the countries.

Keywords: export performance; exchange rate; interest rate; fdi; inflation rate; GDP; ARDL modeling; Granger casualty method

JEL Classification: C22, E4, E31, F31

1. Introduction

BRICS is an imperative alliance, which brings together the foremost emerging economies of the world and is expected to exhibit extraordinarily high economic growth rates over the coming years (Syriopoulos, Makram & Boubaker, 2015). The term BRICs was coined by the British economist Jim O'Neill (2001), Goldman Sachs chief global economist, to describe four major emerging economies of Brazil, Russia, India and China. The extension of group took place at foreign minister's assembly in New York in 2010 with the inclusion of South Africa. BRICS capital markets receive growing global fund inflow as international portfolio investors recognise BRICS markets as a unique asset class to allocate their portfolio

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(Tripathi & Kumar, 2015). A study by Mensi *et al.* (2014) also propose that BRICS countries are the major recipients of international investment flows and are amongst the foremost global consumers of commodities.

In this present scenario, investors, traders, portfolio leaders, monetary experts and governments are keenly interested in understanding the dynamic volatility behaviours of the most widely traded commodities, the stock markets and their inter-connections (Choi & Hammoudeh, 2010). Commodity traders also observe both stock as well as commodity market fluctuations to presume the trend of each market (Creti, Joëts & Mignon, 2013; Gokmenoglu & Fazlollahi, 2015). Numerous studies all around the world examined the affiliation among stock returns and commodity prices, yet there is a dearth of literature scanning this link among developing economies such as BRICS. Much of the previous literature ponder over the volatility of WTI crude oil and give meagre attention to strategic commodities such as Brent crude oil, gold prices and metal prices including Aluminium, Copper, Iron Ore, Lead, Nickel, Tin and Zinc.

To fill this gap, the current study examines the asymmetric impact of commodity prices such as metal prices, oil prices and gold prices on the performance of BRICS stock markets using nonlinear Autoregressive Distributed Lag (NARDL) co-integration approach proposed by Shin, Yu & Greenwood-Nimmo (2014), which is crucial to capture positive as well as negative changes in an independent variable in both the short and long-run (Mensi *et al*., 2016). This model extends the autoregressive distributed lags (ARDL) bounds testing approach of Pesaran, Shin, & Smith (2001) to allow for assessing asymmetric long run as well as short run coefficients in a co-integration framework (Kisswani & Elian, 2017), irrespective of the fact whether the series is integrated at level, first difference or mixed (Ahmad *et al.*, 2019; Rahman & Ahmad, 2019).

It is worth noting that the rate at which a macroeconomic variable respond to upsurge in volatility may be different than the rate at which they react to decline in volatility (Bahmani-Oskooee & Saha, 2019; Qamruzzaman &vJianguo, 2018). However, much of the available literature takes into account the symmetrical impact by using the linear ARDL approach (Al-Tarawneh & Ghazi, 2018; C. Lin, 2012; Musawa & Mwaanga, 2017; Mwaanga & Njebele, 2017). Chang and Kumar, (2018) mentioned in a study that major drawback of earlier studies is that they consider the symmetric effect only by applying the standard co-integration techniques, such as linear autoregressive distributed lag model. Hence, using linear models would not be a suitable approach as it might provide deceptive indication on such association (Alqaralleh, 2020; Kisswani & Elian, 2017). The current study provides new insights by adopting an asymmetric model such as the nonlinear Autoregressive Distributed Lag (NARDL) co-integration approach on the updated dataset of the BRICS stock markets, contrasting the former literature. The study is based on two objectives; the first is to examine the co-integration between stock markets of the BRICS economies and the prominent commodity prices. The second objective is to examine long-run and short-run dynamic relationships between stock markets of the BRICS economies and the commodity prices.

Precisely, the study addresses the following research questions:

RQ1: *Does symmetric or asymmetric co-integration exist between stock markets of the BRICS economies and the prominent commodity prices considered under study?*

RQ2: *Is there any nonlinear long-run and short-run dynamic relationship among stock markets of the BRICS economies and the commodity prices?*

The remainder of the paper is arranged as follows. Section 2 outlines the brief literature review. Section 3 deals with the econometric methodology. Section 4 provides description of data and Section 5 presents and discusses the results. The last segment concludes the paper, providing outcome of all the analysis, reporting notable insights and provide path of future research.

2. Literature Review

The impact of fluctuations in commodity prices such as crude oil price, metal price and gold price on stock returns has continued to draw substantial interests of numerous scholars in recent literature works, as they are considered important resources and have a vibrant presence in supporting the economic and social progress of nations (Aumeboonsuke, 2021). Ample literature is accessible in the field of finance and economics on the dynamic bond between stock returns and a range of commodity variables on different economies over a range of different time horizons. A study conducted by Creti, Joëts, & Mignon (2013) showed that due to the financial turmoil of 2007-08, the correlation between equity and commodity markets has strengthened and suggest that throughout the last decade, commodity prices experienced an exceptional volatility, with simultaneous and alternating phases of rising and falling trends. Mensi *et al*. (2013) also find significant correlation and volatility transmission across commodity and equity markets and confirm that past shocks and volatility of the S&P 500 intensely affect the commodity prices. Similarly, Kaur & Dhiman (2017) examine the link between Indian stock market and commodity market and evince high positive impact of metal commodity returns on the metal stock returns. Similarly, Musawa & Mwaanga (2017) suggest long run significant impact of commodity prices on stock returns.

Furthermore, Narayan & Gupta (2014), Papapetrou (2001), Park & Ratti (2008) analyse the role of oil prices in foreseeing the stock returns and determine that oil price plays a vital role in predicting stock returns. The study also evinces nonlinear predictability, which shows that negative oil prices predict US stock returns more than do positive oil prices. Similarly, Sadorsky (1999) proposes that oil price fluctuations have noteworthy impact on economic activity, though variations in economic activity have little impact on oil prices. Caporale, Ali, & Spagnolo (2014), Gjerde & Saettem (1999) also display that market responds rationally and positively to oil prices. On the contrary, some studies exhibit that international stock market returns do not react in a very significant manner to oil market shocks (Apergis and Miller, 2009; Chen, 2010; Cong *et al*., 2008; Reboredo and Rivera-castro, 2014); therefore, the magnitude of such effects proved to be small. Similarly, other authors (Cunado & Gracia, 2014; Jacobsen & Maat, 2007; Lin, Liang, & Tsai, 2019) confirm that an oil price rise due to a supply shock is expected to have a more negative effect on stock returns than an oil price rise due to a demand shock.

Additionally, Filis (2010) use Hodrick-Prescott (HP) and Baxter & King (BK) series filters to remove cyclical components of time series from raw data and conclude that stock market is adversely inclined by oil prices. In future, Greece should pay more attention to oil price shocks as these shocks influence its stock market. In the same way, Zhang (2017) show inadequate contribution of oil shocks to the world financial system, as these shocks may not be vital on long term, but can occasionally contribute to the international financial system significantly. Oil prices are considered to be a primary macro-economic factor, which generates unstable economic conditions and affect the global financial stability (Naifar & Dohaiman, 2013), whenever major international political and economic events occur, such as government policies, geopolitical risks, investor sentiments and natural disasters *(Lin et al*., 2019).

More so, using quantile regression and MGARCH approach, Ali *et al.*, (2020) explore the association among exchange rate, gold price and the stock market returns and confirm negative impact of exchange rate and gold price volatility on the stock market performance. Singh & Sharma (2018) also find positive correlation among Sensex, gold, crude oil and USD across the three sub-periods, *i.e.,* before, during and post-crisis, and conclude that co-integration and causality relationship among these variables is deeply influenced by the 2008 global financial crisis. Similarly, Shiva & Sethi (2015) suggest that gold serves as a form of protection when financial markets face extreme fluctuations and evidence the fact that in the long run, gold prices are highly influenced by CNX Nifty, while, in the short run, gold prices are affected by exchange rates prevalent in the global market. In addition, using asymmetric DCC model for weekly stock returns of BRICS and gold data over the period 2000 to 2014, Chkili (2016) examines the time-varying correlations between the two assets and checks the efficiency of gold as a hedge for the equity markets. The study finds low to negative correlations during the major financial crises proposing that gold can act as a safe haven against extreme market movements. Using VARMA-BEKK-AGARCH (V-B-A) model and Quantile regression (QR) approach, Beckmann, Berger & Czudaj (2015) also recommended that gold serves as a hedge and a safe haven. However, this ability seems to be market specific. Furthermore, Adewuyi, Awodumi, and Abodunde (2019) evindenced that gold is a safe haven for the Nigerian stock market at low quantiles, but there is no indication of its safe haven property for South Africa equities at any quantile. One more study by and Roubaud (2019) evidenced that in both bearish and bullish gold market situations, gold acts as a diversifier for the stock market, but not as a safe haven. More so, Huang & Kilic, (2018) suggested that gold to platinum prices (GP) proxies predicted the stock returns in time series more efficiently than the other predictors and also suggested greater risk lowers gold and platinum prices.

Furthermore, Jacobsen, Marshall & Nuttawat (2016) evidence that the movements in industrial metal prices, such as aluminium and copper can predict the stock returns and suggest that increasing industrial metal prices is good news for equity markets in recessions; however, it is bad news during expansions. More so, Hu & Xiong (2013) consider copper prices as the barometer of global economic strength and exhibit the fact that rise in copper price can stimulate increase in the Asian equity markets on the following day. Sockin & Xiong (2015) also developed a theoretical framework where the price of industrial commodities such as copper served as a signal for the health of the global economy.

As stated above, the relationships between stock returns and commodities such as oil and gold are well documented in literature using different econometric techniques, but very few studies consider the role of metal prices. Hence, literature suggests the need to take metal prices into consideration. Moreover, much of the available literature has used symmetric models, which are not capable to capture the asymmetrical effects. Therefore, the current study examines the impact of commodity prices such as metal prices, oil prices and gold prices on stock returns of the BRICS economies using asymmetrical model.

3. Data Description

With the intent to attain the predetermined goal of the study, commodity variables such as metal prices (average of Aluminium, Copper, Iron Ore, Lead, Nickel, Tin and Zinc), crude oil price (UK Brent nominal oil price in US dollars per barrel) and gold prices (Gold (UK), 99.5% fine, London afternoon fixing, average of daily rates) in US dollars are selected to examine their impact on selected stock returns with special reference to Sao Paulo Stock Exchange, Moscow Stock Exchange, National Stock Exchange, Shanghai Stock Exchange and Johannesburg Stock Exchange (Dependent variables). Monthly data from 2004M1 to 2020M12 is used, which consists of 204 observations (Table 1). Data on stock prices has been obtained from investing.com and commodity prices have been obtained from pink sheet of World Bank. All the variables are used in logarithmic form. For data analysis, software like EViews 10 and MS Excel are used.

Table 1. Brief Description of Variables

Variable	*Variable Identification*
Dependent Variable (BRICS)	
Sao Paulo Stock Exchange	BVSP
Moscow Stock Exchange	IRTS
National Stock exchange	NIFTY
Shanghai Stock Exchange	SSE
Johannesburg Stock Exchange	FTSE
Independent Variable (Commodity prices)	
Metal Prices	MET
Crude Oil Price	OIL
Gold Prices	GOL

4. Methodology

The study focuses on non-linear autoregressive distributed lag (NARDL) model proposed by Shin *et al.* (2014) to examine the asymmetric impact of changes in commodity prices on stock returns of the BRICS economies both in the long as well as short run. This model is an extension of the linear ARDL model proposed by Pesaran *et al.* (2001), which is based on the symmetric assumption that the explanatory variable linearly influences the dependent variable (Qamruzzaman & Jianguo, 2018). But, in reality the variables move differently to depreciations and appreciations (Nusair, 2016). Thus, autoregressive models relying on linear assumptions may be incompetent in generating asymmetric variations (Alqaralleh, 2020). Hence, the usage of a nonlinear approach in modelling such asymmetry will produce more consistent results (Chang & Kumar, 2018). Moreover, this model provides better outcomes irrespective of whether the variables are integrated of order zero I(0) or one I(1) (Ahmad *et al*., 2019).

On the basis of research variables used in the current study, the generalized form of model can be symbolized as below:

$$\overset{\text{Stock Prices}}{SP_{BRICS}} = \overbrace{MET, OIL, GOL}^{\text{Commodity Index}} \qquad (1)$$

The linear transformation of equation (1) can be represented as follows:

$$lnSP_{BRICS} = \alpha_0 + \beta_1 \ln MET_t + \beta_2 \ln OIL_t + \beta_3 \ln GOL_t + e_t \qquad (2)$$

where: each variable specifies that all the variables are in natural logarithm form, SP_{BRICS} signifies the stock prices of BRICS stock markets, MET indicates metal prices, OIL indicates the crude oil prices and GOL indicates the gold prices. The model coefficients of $\beta_1$to β_3 represent long-run elasticity and e_t is the error correction term.

As non-linear autoregressive distributed lag model is merely an extension of linear ARDL model; hence, the study firstly presents the general form of unrestricted error correction model for linear ARDL which is as follows:

$$\begin{aligned}\Delta\ln SP_t^{BRICS} &= \alpha_0 + \sum_{i=1}^{n}\mu_1\,\Delta\ln SP_{t-i} + \sum_{i=0}^{n}\mu_2\,\Delta\ln MET_{t-i} + \sum_{i=0}^{n}\mu_3\,\Delta\ln OIL_{t-i}\\ &+ \sum_{i=0}^{n}\mu_4\,\Delta\ln GOL_{t-i} + \gamma_0\ln SP_{t-1} + \gamma_1\ln MET_{t-1} + \gamma_2\ln OIL_{t-1} + \gamma_3\ln GOL_{t-1}\\ &+ \omega_t \qquad (3)\end{aligned}$$

Here, Δ is the first difference operator and the coefficients μ_1 to μ_4 and γ_0 to γ_3 denote short-run and long-run coefficients, respectively. In addition, α_0 is the constant term and ω_t represents white noise.

Following the work of Bahmani-Oskooee & Saha (2019, 2020), Chang & Kumar (2018), Lacheheb & Sirag (2019) and Shin *et al.* (2014), the study decomposes the independent variable into two additional sets of series on the basis of positive and negative changes, as follows:

$$POS\ (MET)_t = \sum_{i=1}^{t} lnMET_i^+ = \sum_{i=1}^{t} MAX(\Delta lnMET_i\,, 0)$$

$$NEG\ (MET)_t = \sum_{i=1}^{t} lnMET_i^- = \sum_{i=1}^{t} MIN(\Delta lnMET_i\,, 0)$$

$$POS\ (OIL)_t = \sum_{i=1}^{t} lnOIL_i^+ = \sum_{i=1}^{t} MAX(\Delta lnOIL_i\,, 0)$$

$$NEG\ (OIL)_t = \sum_{i=1}^{t} lnOIL_i^- = \sum_{i=1}^{t} MIN(\Delta lnOIL_i\,, 0)$$

$$POS\ (GOL)_t = \sum_{i=1}^{t} lnGOL_i^+ = \sum_{i=1}^{t} MAX(\Delta lnGOL_i\,, 0)$$

$$NEG\ (GOL)_t = \sum_{i=1}^{t} lnGOL_i^- = \sum_{i=1}^{t} MIN(\Delta lnGOL_i\,, 0)$$

After incorporating the positive and negative changes in the linear ARDL equation (3), the NARDL model used in this study is as follows:

$$\begin{aligned}\Delta\ln SP_t^{BRICS} = {} & \alpha_0 + \sum_{i=1}^{n}\mu_1\,\Delta\ln SP_{t-i} + \sum_{i=0}^{n}\mu_2^+\,\Delta\ln POS(MET)_{t-i} +\\ & \sum_{i=0}^{n}\mu_2^-\,\Delta\ln NEG(MET)_{t-i} + \sum_{i=0}^{n}\mu_3^+\,\Delta\ln POS(OIL)_{t-i} +\\ & \sum_{i=0}^{n}\mu_3^-\,\Delta\ln NEG(OIL)_{t-i} + \sum_{i=0}^{n}\mu_4^+\,\Delta\ln POS(GOL)_{t-i} +\\ & \sum_{i=0}^{n}\mu_4^-\,\Delta\ln NEG(GOL)_{t-i} + \gamma_0\ln SP_{t-1} + \gamma_1^+\ln POS(MET)_{t-1} +\\ & \gamma_1^-\ln NEG(MET)_{t-1} + \gamma_2^+\ln POS(OIL)_{t-1} + \gamma_2^-\ln NEG(OIL)_{t-1} +\\ & \gamma_3^+\ln POS(GOL)_{t-1} + \gamma_3^-\ln NEG(GOL)_{t-1} + \omega_t \qquad (4)\end{aligned}$$

Here, Δ is the first difference operator. ln indicates that all the variables are in natural logarithm form. SP_{BRICS} signifies the stock prices of BRICS stock markets, MET indicates metal prices, OIL indicates the crude oil prices and GOL indicates the gold prices. The coefficients μ_1 to μ_4 and γ_0 to γ_3 denote short-run and long-run coefficients, respectively. In addition, α_0 is the constant term and ω_t represents white noise. Further, n denotes optimal lag, which is determined by the Akaike information criterion (AIC). According to Shin *et al*., (2014), bound test is used to confirm long run co-integration by comparing the f-statistic with the critical value, as proposed by Pesaran *et al*. (2001) under the null hypothesis ($\gamma_0 = \gamma_1^+ = \gamma_1^- = 0$) of no co-integration.

5. Empirical Analysis

5.1. Graphical Analysis and Descriptive Statistics

Movement of stock returns and commodity prices are graphically depicted in Figure 1. It is evident from the graphs that the stock returns experience frequent spikes and drops. In the case of metal and oil prices, there are sudden falls in 2008, 2016 and in the beginning of 2020 due to subprime crisis, global weaknesses and global tension caused by coronavirus, respectively. However, in the case of gold prices, the effect of 2008 crisis is not much evident but the decrease of 2016 is obvious. In other words, the gold prices are much reliable and show increasing trend as compared to other commodity indices.

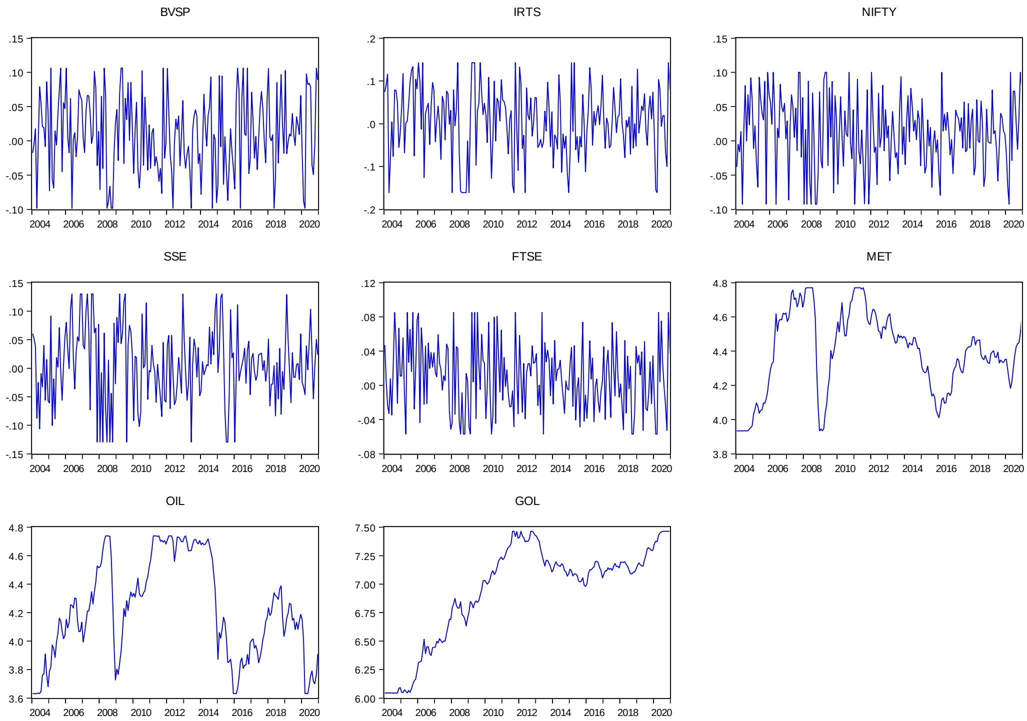
Table 2 presents the descriptive statistics for the series. It is clear from the table that mean return is higher in the case of Indian stock market as compared to other stock markets, followed by Brazil and South Africa. All the market returns vary drastically, but variation is high in the case of Russian stock market. Gold and oil prices also move dramatically, but deviation is quite low in metal prices. Skewness normality tests show that except for South Africa and oil prices, all the return distribution are positively skewed. Kurtosis coefficients point toward that most of the series are platykurtic*, i.e.*, these items are less concentrated near the centre. In addition, the Jarque-Berra test statistics reveal that stock returns of Brazil, Russia, India and China are not normally distributed; however, the stock returns of South Africa and commodity prices are normally distributed.

Table 2. Descriptive Statistics

Variables	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*Jarque-Bera test*
BVSP	0.01004	0.05710	-0.05869	2.18341	[0.0554]
IRTS	0.00620	0.07913	-0.28530	2.54518	[0.1040]
NIFTY	0.01182	0.05170	-0.21301	2.37865	[0.0896]
SSE	0.00630	0.06485	-0.08914	2.67427	[0.5565]
FTSE	0.00959	0.03993	0.14006	2.15136	[0.0335]
MET	4.39204	0.23793	-0.30987	2.22851	[0.0155]
OIL	4.21873	0.34998	0.03250	1.84907	[0.0035]
GOL	6.94975	0.42593	-0.92793	2.70504	[0.0000]

Note: 1. P-value presented between square brackets. 2. The null hypothesis for Jarque-Bera test is that the data is normally distributed against the alternative of data does not come from a normal distribution.

Figure 1. Graphical Representation of Stock Returns of the BRICS Countries and Commodity Prices



5.2 *Correlation Analysis*

Correlation matrix is useful to detect multicollinearity between all the predictor variables and if the correlation is very high, *i.e.,* correlation is above .80 or .90, then there is the problem of multicollinearity (Field, 2009). Table 3 shows that there is no excessive correlation between all the independent variables.

Table 3. Correlation Matrix of Independent Variables

	MET	*OIL*	*GOL*
MET	1	0.7728	0.4119
OIL	0.7728	1	0.3837
GOL	0.4119	0.3837	1

5.3 *Unit Root Test*

A series is said to be stationary if its mean, variance and auto-covariance do not depend on the time factor and satisfies the mean reversion criterion (Bhaumik, 2015). Stationary nature of the data-set is verified using Augmented Dickey-Fuller (ADF) test and Kwiakowski-Phillips-Shmidt-Shin (KPSS) test. The result indicates that stock returns of all the stock markets are stationary at level while commodity variables are stationary at first difference.

Table 4. Unit Root Test

Variables	*ADF test*		*KPSS (LM Stat.)*		*Integration*
	Level	*First difference*	*Level*	*First difference*	
BVSP	(-12.4227)*	-	[0.1254]	-	I(0)
IRTS	(-11.9303)*	-	[0.0861]	-	I(0)
NIFTY	(-14.6887)*	-	[0.0747]	-	I(0)
SSE	(-5.25324)*	-	[0.0428]	-	I(0)
FTSE	(-16.4030)*	-	[0.0484]	-	I(0)
MET	(-2.84253)	(-8.80990)*	[0.1821]	[0.0667]	I(1)
OIL	(-2.71815)	(-10.4114)*	[0.28218]	[0.0549]	I(1)
GOL	(-1.52983)	(-12.3615)*	[0.37122]	[0.1259]	I(1)

Note: t-Statistic presented between parentheses.
For KPSS test, asymptotic critical values are: 1%: 0.216000, 5%: 0.146000.

5.4 *Brock–Dechert–Scheinkma (BDS) Test*

Commodity prices may have non-linear relationship with stock returns due to structural changes in time series data. The study uses the BDS independence test proposed by Broock *et al.* (1996) to test non-linearity dependencies in data. The null hypothesis in the BDS test states that data is independent and identically distributed (iid) against an unspecified alternative. Table 5 shows that null hypothesis in the BDS test with independent and identical distribution is rejected, implying the fact that the time series has nonlinear features under different dimensions.

Table 5. BDS Non-linearity Test Results

BDS statistics					
Series	*Dimension 2*	*Dimension 3*	*Dimension 4*	*Dimension 5*	Dimension 6
BVSP	0.005861***	0.008020	0.011667***	0.014706**	0.015179**
IRTS	0.017751*	0.030187*	0.037198*	0.042659*	0.044265*
NIFTY	0.007072***	0.010268***	0.013389***	0.015297**	0.018828**
SSE	0.009356**	0.022966**	0.036652*	0.045305*	0.049082*
FTSE	0.009748*	0.012682**	0.015152**	0.018707*	0.021582*
MET	0.176306*	0.294283*	0.372234*	0.421238*	0.449996*
OIL	0.167831*	0.280551*	0.352522*	0.396469*	0.421814*
GOL	0.195456*	0.334066*	0.431463*	0.499318*	0.546346*

*Note: Significant codes: *: 1%, **: 5%, ***10%.*

5.5 *Nonlinear Autoregressive Distributed Lag (NARDL)-Bound Test*

Table 6 reports the results of the bounds test of co-integration. Since the value of F-statistics exceeds the bounds critical value at 5% significance level for all the BRICS countries, the null hypothesis of no co-integration is rejected. This means that there is long-run co-integration relationship among stock returns of all the BRICS stock markets and the commodity prices.

Table 6. Bound Test and Wald Test

	BVSP	*IRTS*	*NIFTY*	*SSE*	*FTSE*
F-statistics	13.53627	12.18384	20.31405	5.849149	12.45272

Lower bound value I(0) is 2.45 and upper bound I(1) is 3.61 at 5% level of significance.

It is evident from Table 7 that, in the short run, there is significant impact of lagged stock returns as lagged values of all the stock returns are significant. The asymmetric impact of metal and oil on stock returns of BRICS countries is also much apparent, as the coefficients associated with metal and oil are significant in most of the cases, but there is no evidence of short run asymmetric association between stock returns and gold prices in all the countries. Rise and fall in metal prices mostly affect Brazil, Russia, China and South Africa, whereas oil prices affect all the countries, but mostly the Russian and Chinese stock markets. The table indicates that, in the short run, the Indian market is least affected and the Russian market is highly affected by commodity prices.

In the long run, there is asymmetric impact of metal prices on stock returns of all the countries, except for China. It is only the Chinese market which is least affected by rise or fall in metal prices as stock returns are positive in both cases. In the case of oil prices, positive change has negative influence on Brazil, India and China stock returns and negative change affects negatively Brazil and China. Hence, ups and downs in oil prices show assorted results in all the countries. Gold prices also behave asymmetrically, positive change in gold prices negatively affects all the countries except for Brazil; however, negative change in gold prices has positive effect on Russian, Indian and South African stock returns. It is only the Chinese stock market which shows negative influence of positive as well as negative change in gold prices. Further, it is also evident that, in the long run, it is only the Russian market which is highly affected, as all the commodity indices are significant, whereas for other countries gold is only significant in the case of Indian market.

Table 7. NARDL Estimated Results

	BVSP	*IRTS*	*NIFTY*	*SSE*	*FTSE*
Panel A: Short run results					
C	0.045846*	0.015490	0.053376*	0.002522	0.049258*
SR(-1)	0.605229*	0.471759*	0.150186**	-0.262476**	0.626488*
SR(-2)	0.385458*	0.327554*	-	-0.203822**	0.530561*
SR(-3)	0.282855*	0.236604*	-	-0.194614*	0.431602*
SR(-4)	0.118303***	-	-	-	0.259188*
$\Delta POS\ (MET)_t$	0.241785***	-	-	0.481558*	0.250792*

	BVSP	*IRTS*	*NIFTY*	*SSE*	*FTSE*
$\Delta POS\ (MET)_{t-1}$	0.251308***	0.536445*	-	-	-
$\Delta POS\ (MET)_{t-4}$	-	0.437993**	-	-	0.220945**
$\Delta NEG\ (MET)_{t}$	0.303524**	-	-	0.331844**	0.201018***
$\Delta\ NEG\ (MET)_{t-3}$	-	0.769493*	-	-	0.279367*
$\Delta\ NEG\ (MET)_{t-4}$	-	-0.667933*	-0.332730*	-	-
$\Delta\ POS\ (OIL)_{t}$	-	0.426468*	-	-	-
$\Delta\ POS\ (OIL)_{t-1}$	-	-	-	0.269384**	-
$\Delta\ POS\ (OIL)_{t-2}$	-	-	-	-0.208519***	-
$\Delta\ POS\ (OIL)_{t-3}$	-	-	-	-0.229174**	-
$\Delta NEG\ (OIL)_{t}$	0.172282**	0.342939*	0.172282**	-	0.118774**
$\Delta\ NEG\ (OIL)_{t-2}$	-	-0.264126**	-	-	-0.131599**
$\Delta\ NEG\ (OIL)_{t-3}$	-	-	-	-0.169182***	-
$\Delta\ NEG\ (OIL)_{t-4}$	-	0.241371**	-	-0.192785**	-
$\Delta\ POS\ (GOL)_{t-2}$	-	0.547586*	-	-	-
$\Delta\ POS\ (GOL)_{t-3}$	-	0.461229**	-	-	-
$\Delta\ NEG\ (GOL)_{t-2}$	0.475607**	-	-	-	-
Panel B: Long run results					
POS(MET)	-0.027521	0.013180	0.034006	0.092110	0.018551
NEG(MET)	0.012051	-0.090851*	-0.034986	0.030148	-0.025937
POS(OIL)	-0.001522	0.051053**	-0.007172	-0.032958	0.000318
NEG(OIL)	-0.005994	0.015454	-0.006578	0.007368	0.006645
POS(GOL)	0.009874	-0.145507*	-0.073154***	-0.047117	-0.036390
NEG(GOL)	-0.035746	0.031957	0.006320	-0.056052	0.008945
Panel C: Diagnostics tests					
CointEq(-1)	-1.734173*	-1.657536*	-1.304226*	-0.792784*	-1.998039*
Adjusted R^2	0.538188	0.634043	0.569625	0.568759	0.664985
χ^2 - LM	0.6452	0.1309	0.9430	0.9648	0.7091
χ^2 - H	0.1528	0.2413	0.0806	0.2787	0.0058
RR TEST	0.8750	0.2249	0.3712	0.6446	0.7873
JB TEST	0.474243	0.779668	0.135705	0.138260	0.082161

*Note: Significant codes: *: 1%, **: 5%, ***10%. 2. The lag structure of the model is selected by applying Akaike Information Criterion (AIC). 3. Standard error between parentheses. 4. χ^2 - LM, χ^2 - H, RR test and JB test explain the p-value of the Breusch-Godfrey Serial Correlation LM test, Breusch-Pagan-Godfrey Heteroskedasticity test, Ramsey RESET test and Jarque Bera test of normality, respectively. 5. Some lagged variables are automatically detached in order to select the suitable model specific with applicable lags. 6. SR, MET, OIL and GOL represent stock returns, metal prices, crude oil price and gold price, respectively.*

Finally, the study applies statistical tests to check whether the estimated parameters are reliable. As presented in Panel C of table 7, the speed of adjustment (ECT) exhibits a negative sign and is statistically significant at 1% level, which confirms the presence of the long run relationship among the variables. The value of Adjusted R^2 is higher than 50%, which means model is a good fit. There is no serial correlation and no heteroskedasticity, except for South Africa, where heteroskedasticity is present at 1% level. The result of Ramsey's RESET test also suggests that the relationship between dependent and independent variables is correctly specified. The Jarque-Bera test also indicates that the residuals are normally distributed.

After that, by CUSUM and CUSUMQ test, the long run stability in the parameters is confirmed. It is clear from Figure 2, that all the parameters together exhibit long run stability as the plots lie between the critical boundaries of 5% level of significance. Hence, the model is stable and well specified and designates that the long run and short run parameters have a significant impact on the stock returns of the BRICS economies.

Figure 2. Graphical Representation of CUSUM and CUSUM of Square Test

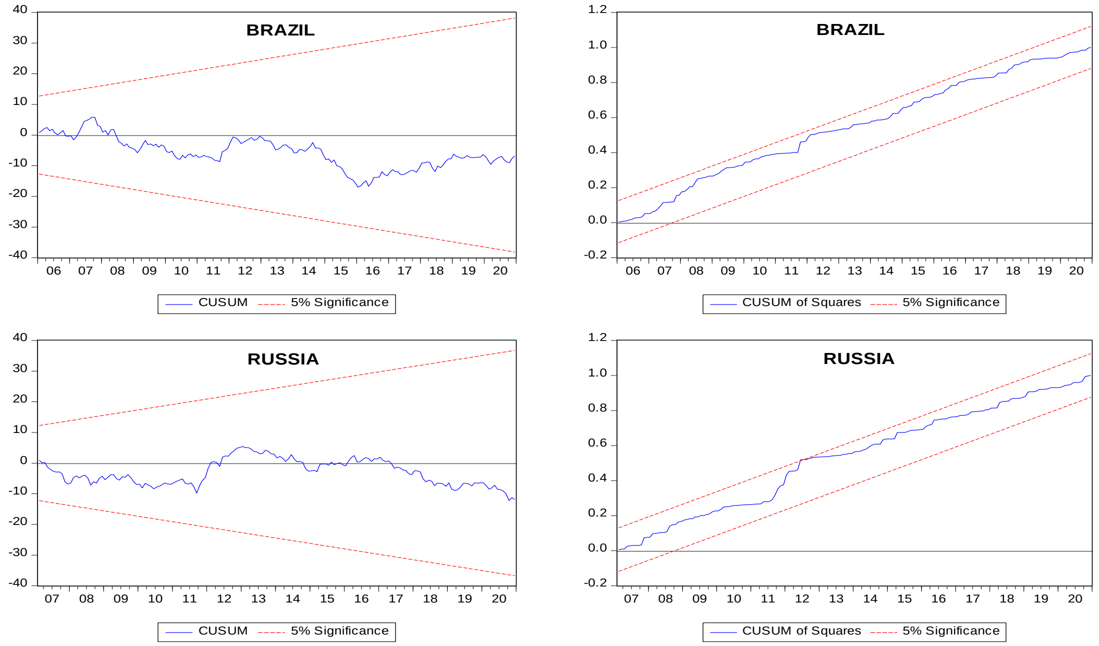


Figure 2. Graphical Representation of CUSUM and CUSUM of Square Test (cont.)

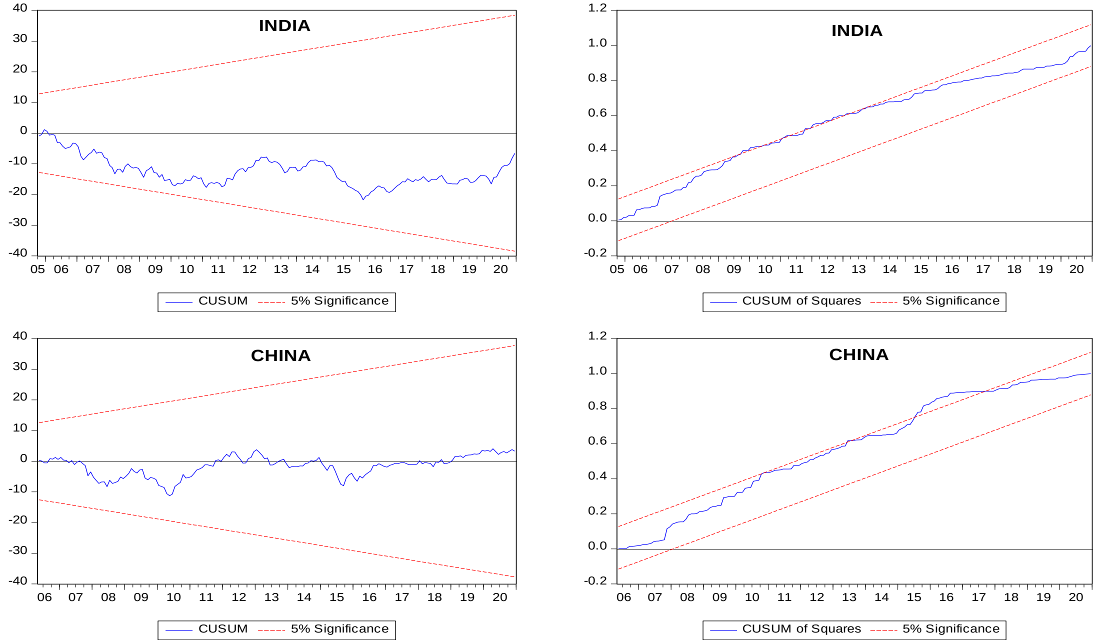
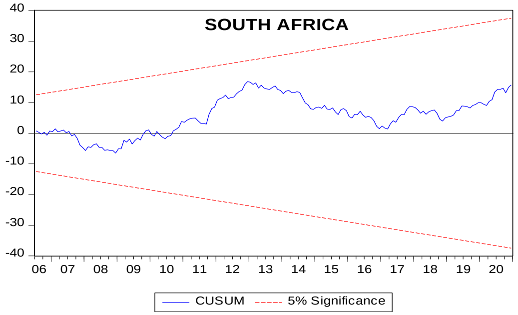
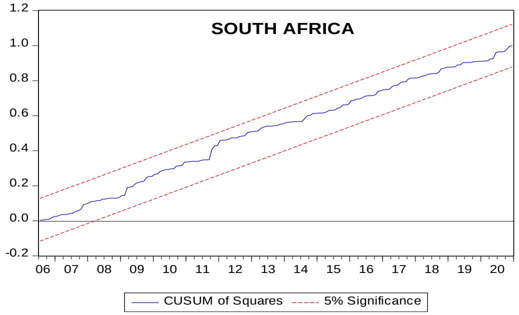


Figure 2. Graphical Representation of CUSUM and CUSUM of Square Test (cont.)





Conclusions

By employing the non-linear Auto Regression distribution lag (NARDL) co-integration test, the study finds that the effects of changes in commodity prices are asymmetric on stock returns of the BRICS economies. In the short run, metal and oil prices have significant impact on all the BRICS stock markets, but there is no such evidence of short run asymmetric association between gold prices and stock returns. Instead, gold prices have significant long run impact on Russian and Indian stock returns. Russian stock market is also significantly affected by metal and oil prices in the long run.

It is observable from the results that the Brazil stock market is mainly influenced by its previous returns and metal prices in the short and in the long run, it behaves asymmetrically to all the variables. Russian stock market is highly affected as the impact of all the commodity prices is significant in the short as well as in the long run. Indian stock market is said to be least affected in the short run, while in the long run it acts asymmetrically and is significantly influenced by positive changes in gold prices. In the case of the Chinese stock market, lagged stock returns, metal and oil prices have significant influence in the short run, while in the long run it behaves asymmetrically to oil prices. The South African stock market is also significantly affected by its own lagged returns, positive change in metal and negative change in oil prices in the short run and behaves asymmetrically to change in metal and gold prices in the long run. In a nutshell, it can be concluded that the Chinese stock market is highly affected in the short run, whereas the Russian stock market is largely influenced in the short as well as in the long run. Hence, the Chinese and Russian governments should pay attention to changes in commodity prices.

Therefore, the application of non-linear ARDL model can provide more appropriate results as all the markets behave asymmetrically to the changes in commodity prices. In the future, further studies can be conducted using other macroeconomic variables, like monetary policy variables or global variables in the context of other countries such as G7 countries or other emerging countries using more advanced econometric techniques like quantile regression or panel NARDL model.

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