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Forecasting stock prices with commodity prices: New evidence from Feasible Quasi Generalized Least Squares (FQGLS) with non-linearities

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ABSTRACT

The complexities in modern stock markets make it imperative to unravel the possible predictors of their future values. This paper thus provides insights into the predictability of stock prices of the BRICS countries with large dependence on commodities either for foreign exchange earnings or industrial while accounting for the role of asymmetries. Essentially, empirical evidence abound for the high volatility in world commodity markets, thus making us to determine if positive and negative changes in commodity prices predict stock prices differently. In addition, unlike the traditional forecast models, our choice of forecast models additionally addresses certain statistical features, including conditional heteroskedasticity, serial dependence, persistence and endogeneity, inherent in the predictors, which have the potential of causing estimation bias. In all, we find evidence in favour of the ability of commodity prices to predict stock prices of Brazil, Russia and South Africa. Also, both the in-sample and out-of-sample forecast performances of the predicted models support asymmetries in a number of commodity prices in each of these three countries. Our results are robust to different data samples and forecast horizons.

1. Introduction

In recent times, the global economy has been experiencing severe fluctuations in aggregate commodity prices. This has made investors to require a continually greater spotlight to commodity prices - by buying commodities and taking absolute positions in commodity future prices. This pattern has accelerated in the last few years (Büyükşahin et al., 2009). According to Loayza et al. (2007), the unprecedented peaks and trends in commodity prices, such as in 2006 and 2008 are specifically bad to developing countries because both imported inputs and final goods are expensive. Furthermore, the irregularity in the revenues of investors tends to reduce investment and subsequently, growth and development.

The consistent fluctuation of aggregate commodity price cycles is of interest to policy makers and stock market participants, having known their major impacts on economic and financial development (Cevik and Saadi-Sedik, 2011). As a result, they pay

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specific awareness to aggregate commodity prices and their variations due to their potential effects on inflation and subsequently prices of stocks. Commodity prices increase as a result of an increase in demand due to thriving economic activities (Kilian and Park, 2009). Since these commodities are largely inputs into production processes (Adekoya and Oliyide, 2020), an increase in their prices leads to a reduction in firm revenue, other things being equal, making the firms to have few shares to allocate (Lombardi and Ravazzolo, 2016). This maps pressure on the stock prices and a consequent fall.

Several studies have been carried out on the relationship between commodity prices and stock prices (see, for instance, Gourene and Mendy, 2018; Soyemi et al., 2017; Musawa and Mwaanga, 2017), with evidence of conflicting results. For example, some of the studies attribute the rise in stock prices to the role of oil and metals commodity prices (see Soyemi et al., 2017; Arfaoui and Rejeb, 2017; Mutau, 2016; Fasanya et al., 2021). Opposing this is the study by Iscan (2015) that empirically concludes that there is no relationship between the commodity prices and stock prices.

Despite the proliferation of studies on the commodity-stock nexus, there are still obvious gaps requiring an empirical attention. To a great extent, energy prices, especially the prices of oil and a few metals, have been linked to stock prices, but insufficient empirical information is available for other classes of commodities. Therefore, this study provides unique contributions to the forecast literature in a number of ways. Firstly, it examines the predictive ability of ten commodity prices, generally categorized under five wide arrays of major world commodity markets (Energy, Agriculture, Fertilizer, Metals & Minerals, and Precious Metals) to predict the movement of stock prices. This makes it the one of the most comprehensive study on stock prices prediction using commodity prices.

Secondly, the analysis is considered for the BRICS countries (Brazil, Russia, India, China and South Africa). There is a motivation to consider these countries. The group consists of countries with large dependence on commodities either for foreign exchange earnings or industrial purposes. For instance, except for China which tends to be a net importer of commodities, others are dominant suppliers of the same. Sinate et al. (2016) provide comprehensive salient information on the commodity export/import status of the BRICS countries. The major exports of Brazil are oil seeds, oleaginous fruits, ores, slag, ash, mineral fuels, oils and meats (summing up to not less than 33.8% of her overall exports in 2015), while oils and its constituents only account for 62.8% of Russia's total exports in 2015, making. India's commodity exports largely constitute pearls, precious and semi-precious metals, mineral fuels, oils and diamonds, accounting for about 44.5% of her total exports in 2015. The commodity export basket of South Africa largely comprises of precious and semi-precious metals, mineral fuels, oils, ores, ash and slag, making a total of about 36.6% of her exports in 2015. China is the only country that is more dependent on commodity imports due to her large manufacturing size. Thus, regardless of the angle it is viewed from, whether from an exporter or importer of commodities, the dependence on commodities has the tendency of making the economies of the countries vulnerable to fluctuations in international commodity prices. This consequently affects the performance of their stock markets following an established link between commodity and stock markets.

Our third contribution is based on the attractions of the preferred predictive approach of the Westerlund and Narayan (2015). It uses a data generating process that has the ability to capture endogeneity and persistence of most commonly used predictors and the information contained in the heteroscedasticity of findings. The technique has been proven to lead to a higher forecasting power, especially for series, such as stock prices, that are typically characterized by conditional heteroscedasticity and serial correlation. It is further suitable for the incorporation of both in-sample and out-of-sample analyses as the strength of any predictive model lies in the performance of its out-of-sample analysis.

Lastly, we uniquely capture asymmetries within our forecast models by decomposing the predictors (commodity prices) into positive and negative changes in order to discover if they predict stock prices differently. Undoubtedly, world commodity markets are highly unstable and volatile due to the effect of frequent external shocks from both demand and supply sources (Fasanya and Awodimila, 2020; Adekoya and Oliyide, 2020). It is thus appropriate to discover if asymmetric forecast analysis outperforms the symmetric forecast, as wrong economic policies and poor investment decisions could result if asymmetries are not considered when they exist in actual fact.

The remainder of this paper is organized thus: Section 2 reviews relevant literature. Section 3 develops the methodology. Section 4 describes the data and their statistical features. Section 5 presents and discusses the results. Section 6 gives the concluding remarks.

2. Brief review of literature

In the literature on the relationship between stock prices and commodity prices, a considerable number of studies has been carried out in many countries using different econometric techniques such as Vector Auto regression (VAR), Vector Error Correction Model (VECM), Generalized Autoregressive Conditional Heteroscedasticity (GARCH), Heterogeneous Autoregressive (HAR) model, Ordinary Least Square (OLS), Simultaneous model, Nonlinear Autoregressive Distributed Lag (NARDL) model, etc.

In order to examine the dynamic relationship between stock prices and commodity prices, Iscan (2015) uses the multivariate Johansen test and finds no relationship between commodity prices and stock prices. This finding is similar to that of Ildirar and Iscan (2016). In order to analyze the dynamic relationship between stock prices and commodity prices, Ildirar and Iscan (2016) use the multivariate Johansen test on Central Asian countries with the evidence of no relation between commodity prices and stock markets. For the United States, Benkraiem et al. (2018) consider the stock market reactions to energy prices shocks using the quantile autoregressive distributed lags model. The study proves that the long-run relationship between US energy prices and stock prices is not insignificant across all the quantiles, although oil and natural gas prices are important determinants of stock market returns both in the short and long-run. The bivariate GARCH model was used by Baldi et al. (2016) to study stock markets' bubbles burst and volatility spillovers in agricultural commodity markets in the United States and observe a rising interrelationship between agricultural commodity and stock market.

Yahya et al. (2013) examine the link between gold prices, oil prices and Islamic stocks using the impulse response function (IRF) and variance decomposition analysis from in Malaysia. From their findings, there exists a bi-directional causality relationship between Islamic stock prices with oil prices. In a study conducted by Kang et al., (2017) on the global commodity prices and global stock volatility shocks in Australia, Brazil, Canada, China, France, India, Italy, Japan, Mexico, Russia, South Korea, South Africa, United Kingdom and United. Using a Structural VAR model with time varying coefficient, they conclude that shocks to global commodity prices have positive effects on global stock volatility that are statistically significant and persistent. This is also echoed by Sadorsky (1999) which highlights the importance of oil in explaining the movements of other variables. Arfaoui and Rejeb (2017) examine the relationship between oil, gold, and stock prices in China using simultaneous equations system. Their results reveal significant interactions between all the variables, particularly a negative nexus between oil and stock prices.

A reasonable number of studies have equally been examined on African stocks. For example, Gourene and Mendy (2018) investigate the co-movement between oil prices and African stocks using the continuous wavelet transform model, and discover a weak co-movement in the short and medium term horizons. The exemptions to this evidence are South Africa and Egypt stock markets. In another recent study for Zambia, Musawa and Mwaanga (2017) use the ARDL model and the VECM to investigate the effect of commodity prices interest rates, and exchange rates on the stock price index. The findings of the study reveal that interest rates, exchange rates, copper and oil price have a long and short run impact on that Lusaka Stock Market.

In addition, Mutua (2016) investigated the effect of macroeconomic variables and global oil prices on the stock performance of all listed firms in Kenya. Using the linear regression models, a negative correlation is observed between stock price index and global oil prices. For Ghana, Gyasi (2016) confirms through the VAR-GARCH-BEKK model that there is a strong bidirectional relationship between stock market performance and crude oil prices. The study of Soyemi et al. (2017) takes a more robust approach by looking into the nexus between oil and stocks at the firm-level of the latter for Nigeria. Concluding from the Exponential GARCH model used, oil shocks have a direct positive and indirect effect on firms' stock prices.

Some empirical evidence are also available for the BRICS economies. Examining the impact of oil price shocks on three BRICS countries' stock prices, the structural VAR model explored by Fang and You (2014) reveals that global oil production shock has no significant effects on the stock markets of India, Russia and China stock market, but global demand shocks significantly affect Russian stock market. However in another study, Mensi et al. (2018) analyze the time frequency co-movements across gold and oil prices with BRICS' stock markets based on the VAR wavelet approach. The findings from the study suggest that there is an evidence of co-movements between commodity (oil and gold) prices and stock prices of the BRICS countries.

There is no doubt that the literature on the relationship between commodity prices and stock markets has been well studied with mixed findings. However, the predictive power of commodity prices in forecasting stock prices is still limited. In our paper, we provide an alternative approach which accounts for the hidden characteristics of the relevant variables in the predictive model. As such, we hypothesize that such consideration which has been a daunting task in the literature will produce desirable results for forecasting stock prices with commodity prices.

3. Econometric methodology

This study makes use of Westerlund and Narayan (2015) approach. The framework uses data generating process for its ability to capture endogeneity, persistence of most commonly used predictors and information contained in the heteroscedasticity of findings. Accounting for this, in addition to serial correlation, is expected to lead to a higher forecasting power.

3.1. The model

To evaluate the predictive nexus between stock prices and commodity prices, we start the methodology by specifying a predictive model following the approach of Westerlund and Narayan (2012, 2015) as follows:

$$s_t = \alpha + \varnothing c_{t-1} + \varphi(c_t - \upsilon c_{t-1}) + \varepsilon_t \tag{1}$$

where s_t is the natural log of stock prices and c_t is the natural log of commodity prices. υ is the first order autocorrelation coefficient. The first term of the model (ϕc_{t-1}) ordinarily captures the bivariate representation of a predictive model. However, the inclusion of the second term ($c_t - \upsilon c_{t-1}$) captures any inherent persistent effect in the predictive model. Accounting for persistence effect may be valid when dealing with high frequency predictors as they may exhibit random walk, where the AR(1) coefficient approximates to one ($\upsilon = 1$). Hence, it is necessary to pre-test series for persistence and account for it if found evident. Following Westerlund and Narayan (2014), the persistence equation is given as:

$$c_t = \varphi(1 - \upsilon) + \upsilon c_{t-1} + v_t \tag{2}$$

where $v_t = N(0, \sigma_v^2)$. In addition, the presence of statistically significant persistence effect may introduce endogeneity bias as a result of possible correlations between the predictor (c_t) and the regression error, ε_t. Therefore, this study tests for endogeneity using the equation:

$$\varepsilon_t = \delta v_t + \mu_t \tag{3}$$

where ε_t and v_t are the error terms from [1] and [2] respectively. The parameter δ captures the endogeneity effect, and if statistically significant, it indicates the presence of endogeneity effect. Therefore, estimating [1] using ordinary least squares (OLS) method will correct for possible endogeneity bias, and it will yield a bias-adjusted OLS estimator for α. This is described as:

$$\hat{\beta}_{adj} = \hat{\beta} - \varphi(\hat{\upsilon} - \upsilon) \tag{4}$$

To account for the Autoregressive Conditional Heteroscedasticity (ARCH effect), Westerlund and Narayan (2012, 2015) propose a Feasible Quasi Generalised Least Squares (FQGLS) estimator which considers the information contained in the heteroscedasticity variance of the regression residuals to generate more precise estimates. The regression error in [1] is assumed to follow an ARCH structure given as:

$$\hat{\sigma}^2_{\varepsilon,t} = \mu + \sum_{i=1}^{q} \rho_i \hat{\varepsilon}^2_{t-i} \tag{5}$$

The resulting $\hat{\sigma}^2_{\varepsilon,t}$ is then used as weight in the predictive model. Thus, the estimator can be described as a GLS-based t-statistic for testing $\alpha = 0$ is given as:

$$t_{FQGLS} = \frac{\sum_{t=q_m+2}^{T} \hat{\tau}_t^2 s_t^d c_{t-1}^d}{\sqrt{\sum_{t=q_m+2}^{T} \hat{\tau}_t^2 (c_{t-1}^d)^2}} \tag{6}$$

where $\hat{\tau}_t = 1/\hat{\sigma}_{\varepsilon,t}$ is used in weighing all the data for the series in the predictive model, $s_t^d = s_t - \sum_{s=2}^{T} s_t/T$ and $c_t^d = c_t - \sum_{c=2}^{T} c_t/T$.

As formerly discussed, this study accounts for asymmetries in each of the predictors in Eq. (1) by decomposing all the selected commodity prices into positive and negative changes. This approach is a novel extension to the original method of Westerlund and Narayan (2015), but has been uniquely considered in subsequent studies (see Fasanya and Awodimila, 2020). The resulting equations from (1) are given respectively for positive changes in commodity prices (c_t^+) and negative changes (c_t^-) as:

$$s_t = \alpha^+ + \varnothing^+ c_{t-1}^+ + \varphi^+ (c_t^+ - \vartheta c_{t-1}^+) + \varepsilon_t^+ \tag{7a}$$

$$s_t = \alpha^- + \varnothing^- c_{t-1}^- + \varphi^- (c_t^- - \vartheta c_{t-1}^-) + \varepsilon_t^- \tag{7b}$$

Following Shin et al. (2014), the computation procedure for c_t^+ and $c_t^-$and follows as a partial sum decomposition of positive and negative Commodity prices changes and it is given below as:

$$c_t^+ = \sum_{j=1}^{t} \Delta c_{ij}^+ = \sum_{j=1}^{t} \max(\Delta c_{ij}, 0) \tag{8a}$$

$$c_t^- = \sum_{j=1}^{t} \Delta c_{ij}^- = \sum_{j=1}^{t} \min(\Delta c_{ij}, 0) \tag{8b}$$

There is evidence of asymmetric effect of commodity prices on stock prices if the either or both the coefficients of $c_t^+$and c_t^- are statistically significant. Otherwise, symmetrical effect is the case.

3.2. Forecast evaluation

The forecast evaluation is carried out for both the in-sample and out-of-sample periods. As it is popular in extant literature, this study will use the 50% and 75% observations of the full-sample for the forecast evaluation following the rolling window approach which accounts for the time-varying behaviour in the stock prices-commodity prices relationship to produce the forecast results (see Narayan and Gupta, 2014; Bannigidadmath and Narayan, 2016; Salisu and Isah, 2018). We begin with the evaluation of the in-sample predictability of the model using the Root Mean Square Error (RMSE), computed as:

$$RMSE = \sqrt{1/T \sum_{i=1}^{r} (\hat{c}_t - c_t)^2} \tag{9}$$

where $\hat{c}_t$ and c_t denote the fitted and actual values of commodity prices respectively.

Having estimated these forecast models, their performances are compared afterwards with the preferred model in Eq. (1) using the Campbell-Thompson (C-T).

The C-T test is computed as:

$$[1 - (M\hat{S}E_1/M\hat{S}E_0)] \tag{10}$$

where the $M\hat{S}E_1$and $M\hat{S}E_0$ are the mean square error (MSE) of the prediction from the unrestricted and restricted models, respectively.[1] A positive value of the statistic suggests that the unrestricted model outperforms the restricted model; otherwise, it does not.

[1] The restricted model in this case is the autoregressive model while the unrestricted model is the asymmetric model estimated using Westerlund and Narayan (2015) estimator.

4. Data and preliminary analyses

4.1. Sources of data

This study adopts the world monthly prices of beverages (BEV), crude oil (BRT), oil and meals (OM), fertilizer (FER), grains (GRA), metal and mineral (MM), other food (OF), timber (TIM), other raw material (ORM), precious metal (PM) and stock (STK). The data of all the selected commodity prices are obtained from World Bank Commodity Price Data, while the stock price index of the selected countries, Brazil (01/1994 – 09/2018), Russia (09/1995–09/2018), India (01/1994 – 09/2018), China (04/2005 – 09/2018) and South Africa (06/2002 – 09/2018) are sourced from DataStream and Global Economic Monitor. The data scope varies across the countries due to data availability.[2]

4.2. Preliminary analyses

Following the common practice in the extant literature, we briefly highlight the descriptive properties of the series and further rationalize our chosen empirical technique. As seen in Appendix Table 1 A, statistic shows that South Africa has the highest average stock price with a value of $91.80, followed by China ($88.54). However, notwithstanding the fact that Brazil records the least average stock price, its stock market seems to be less volatile, compared to South Africa that has the largest average price, judging by the standard deviation statistic. In fact, starting from the rear, Brazil ranks next to China in terms of stock market volatility. Russia seems to have the most volatile stock market given its standard deviation value of 46.35. Turning to the commodity prices, their descriptive statistics are explained from the angle of the countries with the largest sample (Brazil and India) only, since they are world prices. Therefore, it could be seen that the highest mean price of $86. 74 goes to timber, while Brent oil price records the least value of $52.97. In terms of volatility, timber and fertilizer enjoy the highest and least volatilities respectively. The volatile nature of the series and the co-movement between the commodity and stock prices are further confirmed by the graphical trends in Figs. 1–5 in the Appendix.

The values of the skewness and kurtosis statistics also significantly deviate from the standard thresholds of zero and three (3), indicating the non-normal distribution of the series. More so, all the series are found to be stationary only after the first difference as revealed by the Augmented Dickey-Fuller (ADF) test.

The final part of the preliminary analysis is devoted to the essential conditions for the consideration of the predictive model of Westerlund and Narayan (2015). The last two columns of Table 1 A suggests that all the predictors exhibit high level of persistence as their first-order autoregressive coefficients are significant and close to one (1). However, endogeneity is not found to be significant in most cases, suggesting that it has no tendency of imposing any bias on the predictability of stock prices. Table 1B presents the results for serial correlation and heteroscedasticity with significant evidence found for both regardless of the lags considered.

5. Discussion of results

The presentation and discussion of the predictability test results lead this section. The idea is to first determine if the predictors matter in predicting the stock prices of the BRICS countries. Following this, we examine the forecast accuracy of the significant potential predictors. Since the strength of a forecasting model lies in the outcome of its out-of-sample analysis, we ensure that our results are robust by extending our forecast analysis to the out-of-sample analysis. Furthermore, the analysis is evaluated for different sub-samples (50% and 75%). Concluding this section, we offer comparative assessment of the model with the best forecast performance between the symmetric and asymmetric model, and consequently with the traditional model.

5.1. Predictability test results

As earlier pointed out, the forecast model of Westerlund and Narayan (2012, 2015) is most suitable estimator for determining the predictive power of a variable in the presence of certain unpalatable statistical characteristics including autocorrelation, heteroscedasticity, and high degree of persistence, among others. In short, this approach has the ability to deal with the likely biasness that could be generated by these features exhibited by the series (see Salisu and Isah, 2018). In light of this, the GLS estimates that have been adjusted for possible bias through our chosen technique is presented in Tables 1 A 1B. The results seem to be sensitive to different sub-samples, although unanimous conclusions are deduced from both the 50% and 75% estimates in a number of ways. It could be seen that there is consistent insignificance of the coefficients of commodity prices on the stock prices of India and China irrespective of the sub-sample. On the other hand, only the price of minerals and metals seem to be insignificant in both cases (50% and 75%) for Brazil and South Africa in addition to oil price for the latter country.

Interestingly, it is observed in all the cases where commodity prices are found to be significant predictors of stock prices that the coefficients are positive. Although conflicting evidences as regards the nature of the correlation between commodity prices and stock prices are established, our predictability results yet support notable studies such as Arfaoui and Rejeb (2017) and Mutau (2016) that believe that increase in stock prices is due to the thriving nature of the commodity prices market. On the other hand, the poor predictive ability of the commodity prices on the stock prices of India and China is also supported by the study of Iscan (2015) which finds similar evidence for Turkey.

[2] The data are available with the corresponding author upon reasonable request.

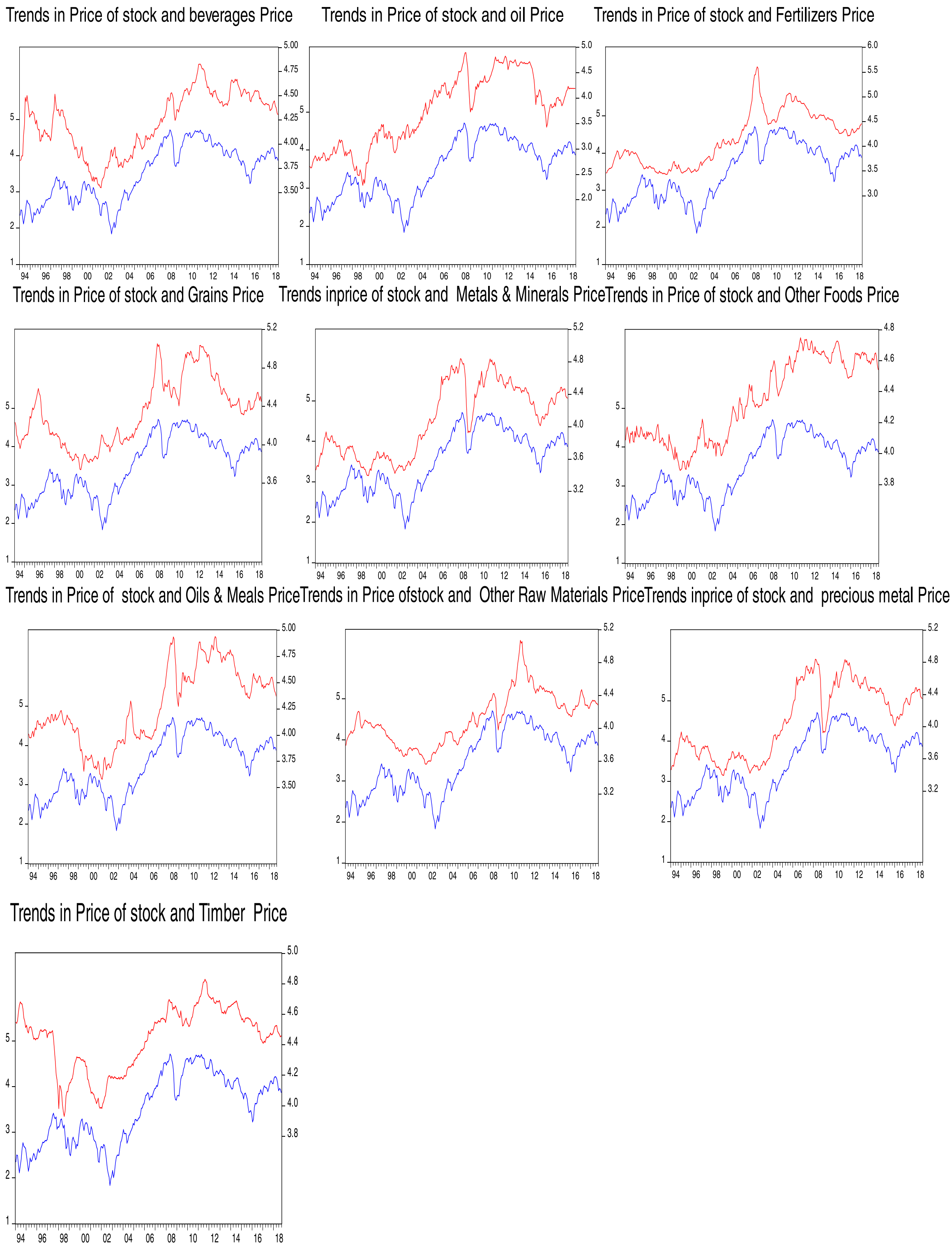

Fig. 1. Trends in Commodity Prices and Stock Prices of Brazil.

5.2. Forecast evaluation results

Having revealed through the predictability test that the commodity prices are valid predictors of stock prices in three of the BRICS countries namely Brazil, Russia and South Africa, we proceed to the evaluation of their forecast performance. Basically, we evaluate the

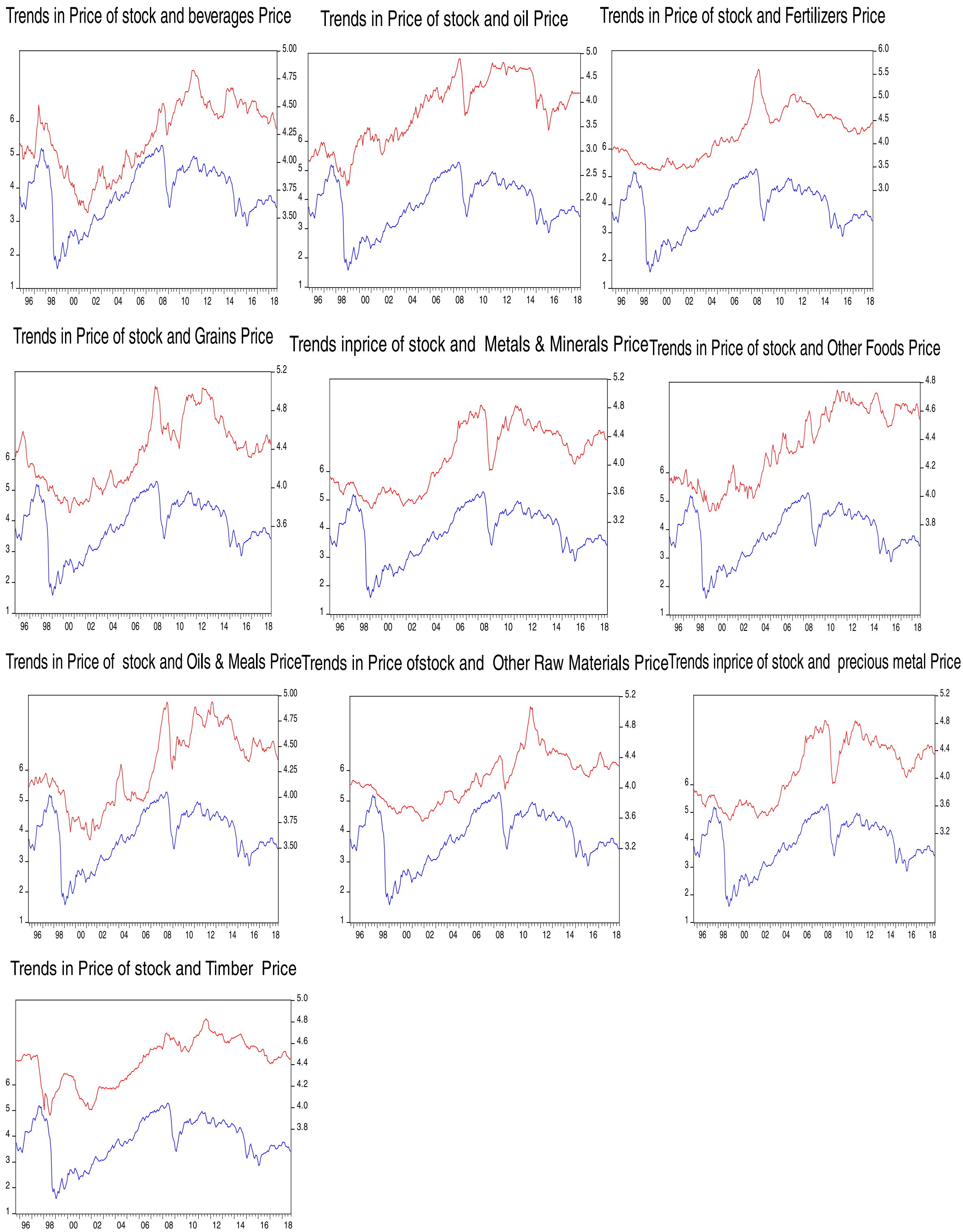

Fig. 2. Trends in Commodity Prices and Stock Prices of Russia.

forecast performance for both the in-sample and out-of–sample analyses. Also, premised on our desire to determine if asymmetries matter in the ability of commodity prices to forecast stock prices in these countries, we extend the forecast models to accommodate asymmetries.

Conventionally, we begin the discussion with the in-sample forecast results (see Tables 2–4). Considering the results for the 50% sub-sample, the estimates based on the RMSE indicate that the stock prices of each country are sensitive to the kind of commodity

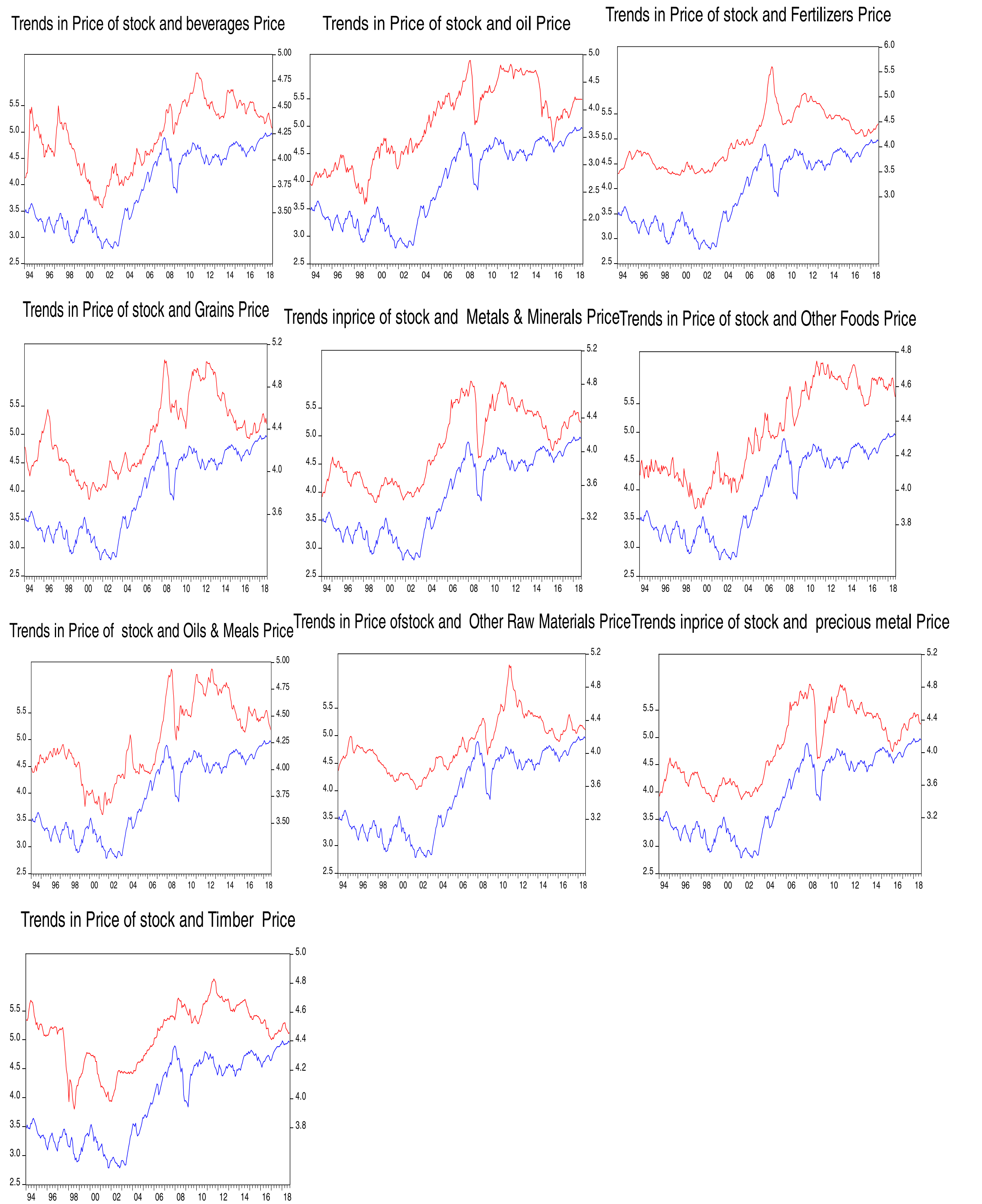

Fig. 3. Trends in Commodity Prices and Stock Prices of India.

prices, as the best predictive model significantly alternate between the symmetric and asymmetric model. For instance, the RMSE value for the asymmetric predictive model is lower for only five commodity prices in Brazil namely beverages, oil & meals, grains, other foods and minerals and metals. This indicates that the asymmetric commodity price-based predictive model outperforms the symmetric commodity price-based predictive model in only five commodity prices, and otherwise for the remaining. In the case of

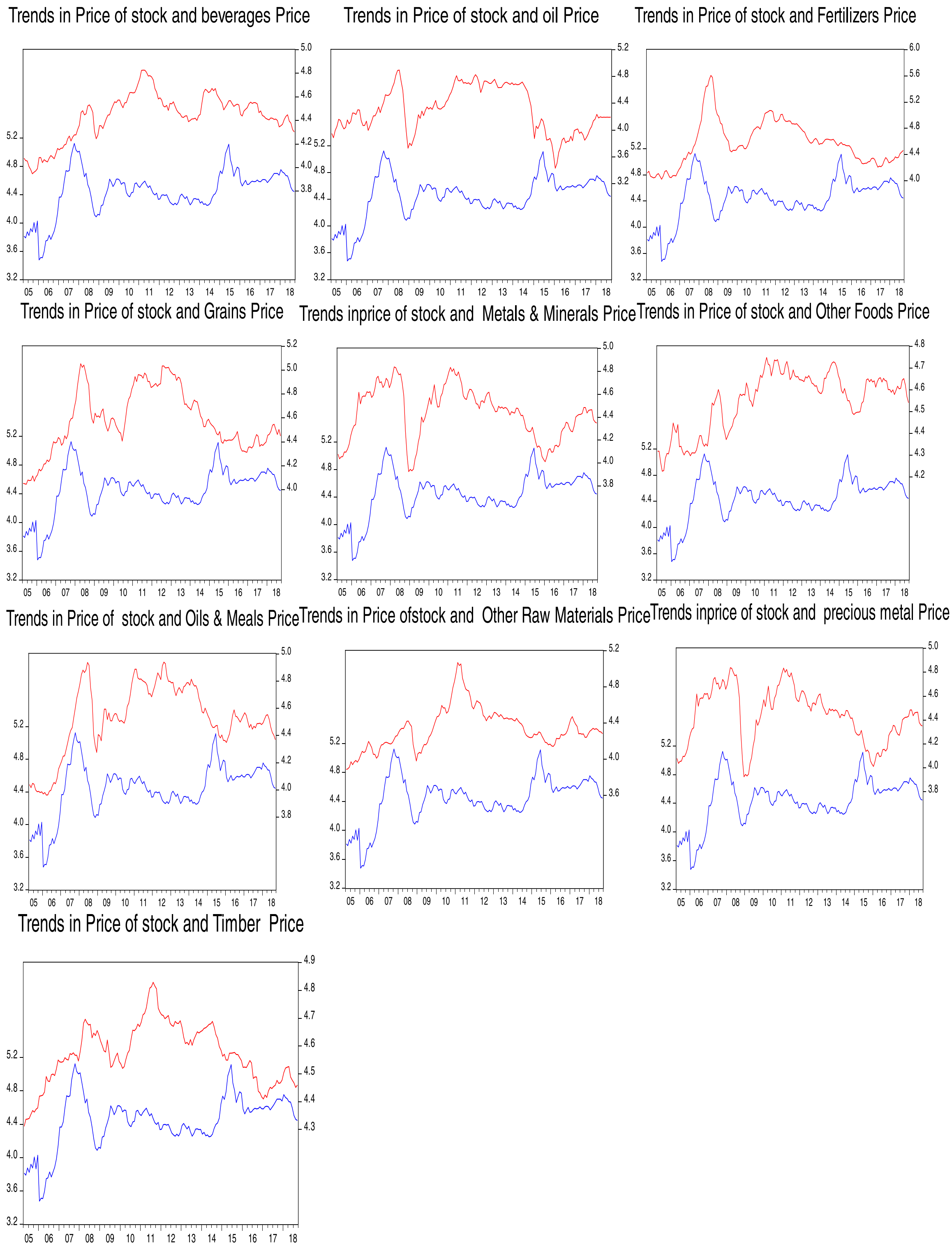

Fig. 4. Trends in Commodity Prices and Stock Prices of China.

Russia and South Africa, the asymmetric model only outperforms the symmetric model in four and six commodity prices respectively. However, the results seem inconclusive in few instances when the RMSE value is the same for both the symmetric and asymmetric model. Then, we confirm the in-sample results with the out-of-sample estimates.

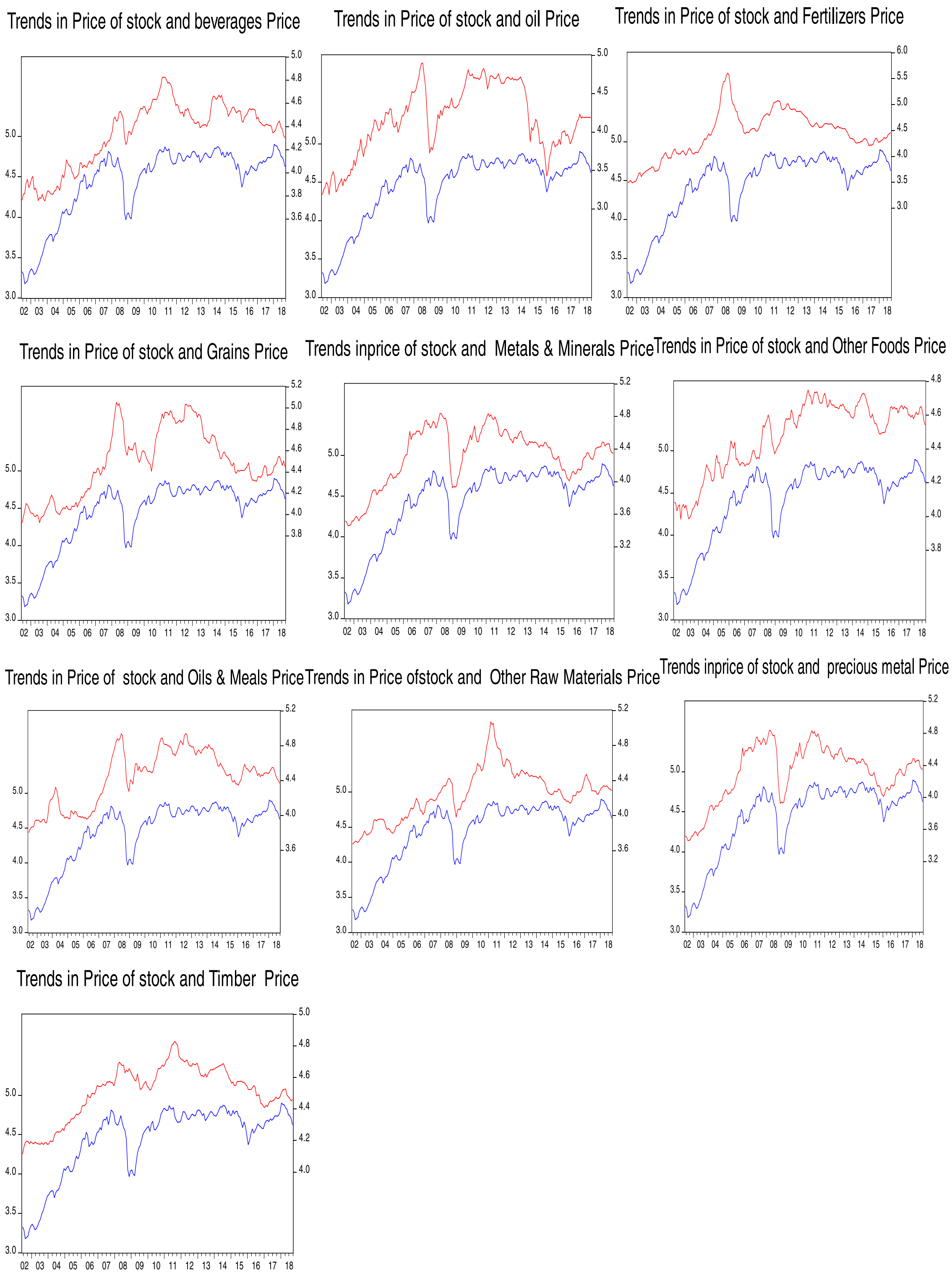

Fig. 5. Trends in Commodity Prices and Stock Prices of South Africa.

Table 1 A
Predictability tests results for 50% of the full sample.

Commodities	Brazil	Russia	India	China	South Africa
BEV	0.0049 **	0.0073 ***	0.0007	-0.0005	0.0018 **
	(0.0024)	(0.0019)	(0.0013)	(0.0025)	(0.0009)
BRT	0.0072 **	0.0074 ***	0.0014	-0.0024	0.0011
	(0.0030)	(0.0023)	(0.0017)	(0.0023)	(0.0009)
OM	0.0048 *	0.0071 ***	0.0007	-0.0008	0.0016 *
	(0.0025)	(0.0020)	(0.0014)	(0.0023)	(0.0009)
GRA	0.0048 **	0.0072 ***	0.0006	-0.0009	0.0021 **
	(0.0024)	(0.0020)	(0.0013)	(0.0022)	(0.0009)
OF	0.0048 **	0.0068 ***	0.0004	-0.0005	0.0022 **
	(0.0023)	(0.0020)	(0.0013)	(0.0025)	(0.0009)
TIM	0.0049 **	0.0069 ***	0.0007	0.0009	0.0022 **
	(0.0022)	(0.0018)	(0.0012)	(0.0024)	(0.0009)
ORM	0.0049 *	0.0080 ***	0.0006	-0.0005	0.0017 *
	(0.0026)	(0.0023)	(0.0014)	(0.0023)	(0.0009)
FER	0.0057 **	0.0078 ***	0.0009	-0.0007	0.0021 **
	(0.0026)	(0.0021)	(0.0015)	(0.0024)	(0.0009)
MM	0.0031	0.0051 **	8.12E-05	-0.0019	0.0010
	(0.0025)	(0.0020)	(0.0014)	(0.0022)	(0.0008)
PM	0.0056 **	0.0066 ***	0.0002	-0.0024	0.0017 *
	(0.0025)	(0.0018)	(0.0015)	(0.0031)	(0.0009)

* ** , * * and * suggest the rejection of the null hypothesis of absence of predictability at 1%, 5% and 10% significance levels respectively. The values in parentheses are standard errors. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal.

Table 1B
Predictability tests results for 75% of the full sample.

Commodities	Brazil	Russia	India	China	South Africa
BEV	0.0032 *	0.0045 **	0.0008	-0.0008	0.0021 *
	(0.0017)	(0.0018)	(0.0011)	(0.0015)	(0.0011)
BRT	0.0030	0.0025	0.0007	-0.0012	0.0013
	(0.0019)	(0.0019)	(0.0013)	(0.0015)	(0.0012)
OM	0.0018	0.0034 **	0.0006	-0.0009	0.0020 *
	(0.0017)	(0.0017)	(0.0011)	(0.0014)	(0.0011)
GRA	0.0032 *	0.0052 ***	0.0008	-0.0007	0.0031 ***
	(0.0017)	(0.0017)	(0.0011)	(0.0014)	(0.0011)
OF	0.0034 **	0.0049 ***	0.0008	-0.0007	0.0021 *
	(0.0015)	(0.0017)	(0.0011)	(0.0015)	(0.0011)
TIM	0.0040 **	0.0051 ***	0.0009	-0.0004	0.0037 ***
	(0.0017)	(0.0016)	(0.0011)	(0.0016)	(0.0010)
ORM	0.0028	0.0037 **	0.0006	-0.0002	0.0023 *
	(0.0019)	(0.0017)	(0.0012)	(0.0014)	(0.0012)
FER	0.0033 *	0.0056 ***	0.0009	-0.0007	0.0039 ***
	(0.0018)	(0.0017)	(0.0012)	(0.0014)	(0.0010)
MM	0.0010	0.0021	1.77E-05	-0.0007	0.0013
	(0.0015)	(0.0015)	(0.0011)	(0.0013)	(0.0009)
PM	0.0027	0.0039 **	0.0003	-0.0008	0.0021 *
	(0.0019)	(0.0019)	(0.0012)	(0.0015)	(0.0012)

* ** , * * and * suggest the rejection of the null hypothesis of absence of predictability at 1%, 5% and 10% significance levels respectively. The values in parentheses are standard errors. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal.

In all the cases where the in-sample analysis supports the superiority of the asymmetric model, the out-of-sample estimates further strengthens the conclusion. Adding to this, the out-of-sample analysis further shows that although the result is inconclusive for oil price for South Africa under the in-sample analysis, the asymmetric oil-price model is superior to its symmetric version in predicting the stock prices of the same country. The in-sample and out-of-sample RMSE results for the 75% sample seem to further strengthen our findings. In fact, the asymmetric commodity price-based predictive model performs better when a larger sample is used as the RMSE values are found to be lower for the asymmetric model in a number of commodity prices more. For instance, the price of timber is additionally found for Brazil, other foods for Russia, and oil and other raw materials for South Africa.

Table 2
Forecast performance results for Brazil.

	WN predictive model				WN_ASY predictive model			
	In-sample RMSE	*Out-of-sample RMSE*			*In-sample RMSE*	*Out-of-sample RMSE*		
		h = 6	*h* = 12	*h* = 18		*h* = 6	*h* = 12	*h* = 18
Using 50% data sampled								
BEV	0.1105	0.1093	0.1075	0.1069	0.1104	0.1091	0.1074	0.1066
BRT	0.1106	0.1096	0.1080	0.1077	0.1109	0.1098	0.1081	0.1076
OM	0.1108	0.1096	0.1079	0.1074	0.1105	0.1092	0.1076	0.1071
GRA	0.1109	0.1097	0.1081	0.1076	0.1108	0.1097	0.1081	0.1077
OF	0.1101	0.1086	0.1070	0.1066	0.1092	0.1077	0.1065	0.1059
TIM* *	0.1104	0.1093	0.1077	0.1073	0.1105	0.1094	0.1078	0.1074
ORM* *	0.1108	0.1097	0.1080	0.1076	0.1104	0.1094	0.1077	0.1071
FER* *	0.1110	0.1099	0.1083	0.1079	0.1115	0.1105	0.1088	0.1086
MM	–	–	–	–	–	–	–	–
PM	0.1096	0.1081	0.1063	0.1054	0.1097	0.1082	0.1063	0.1055
Using 75% of the data sample								
BEV	0.1041	0.1028	0.1023	0.1017	0.1038	0.1027	0.1021	0.1015
BRT	0.1047	0.1035	0.1030	0.1024	0.1048	0.1035	0.1032	0.1027
OM	0.1023	0.1011	0.1008	0.1001	0.1015	0.1005	0.1005	0.0992
GRA	0.1053	0.1042	0.1038	0.1031	0.1051	0.1039	0.1036	0.1030
OF	0.1038	0.1026	0.1022	0.1015	0.1033	0.1021	0.1018	0.1012
TIM* *	0.1064	0.1052	0.1048	0.1042	0.1063	0.1050	0.1048	0.1042
ORM* *	0.1043	0.1031	0.1025	0.1019	0.1044	0.1033	0.1027	0.1020
FER* *	0.1061	0.1048	0.1044	0.1037	0.1051	0.1039	0.1038	0.1033
MM	–	–	–	–	–	–	–	–
PM	0.1035	0.1023	0.1016	0.1008	0.1040	0.1028	0.1021	0.1014

WN represents obtained estimated values from the conventional Westerlund and Narayan (2012, 2015) approach to estimating commodity prices predictability of stock prices, while WN_ASY represents the extended version denoting obtained estimates from our proposed asymmetric commodity prices predictability of stock prices. The smaller the RMSE value, the better the forecasting accuracy of a predictive model. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal.

Table 3
Forecast performance results for Russia.

	WN predictive model				*WN_ASY predictive model*			
	In-sample RMSE	*Out-of-sample RMSE*			*In-sample RMSE*	*Out-of-sample RMSE*		
		h = 6	*h* = 12	*h* = 18		*h* = 6	*h* = 12	*h* = 18
Using 50% data sampled								
BEV	0.1738	0.1706	0.1677	0.1663	0.1720	0.1692	0.1664	0.1652
BRT	0.1739	0.1706	0.1676	0.1659	0.1725	0.1697	0.1669	0.1660
OM	0.1748	0.1717	0.1687	0.1671	0.1753	0.1720	0.1690	0.1675
GRA	0.1747	0.1715	0.1685	0.1670	0.1752	0.1721	0.1691	0.1677
OF	0.1732	0.1700	0.1672	0.1657	0.1744	0.1712	0.1684	0.1668
TIM	0.1746	0.1714	0.1684	0.1669	0.1749	0.1717	0.1687	0.1674
ORM	0.1743	0.1711	0.1682	0.1666	0.1681	0.1654	0.1628	0.1620
FER	0.1746	0.1714	0.1684	0.1671	0.1783	0.1751	0.1722	0.1708
MM	0.1706	0.1675	0.1649	0.1630	0.1697	0.1668	0.1643	0.1627
PM	0.1737	0.1704	0.1679	0.1659	0.1740	0.1707	0.1681	0.1662
Using 75% of the data sample								
BEV	0.1594	0.1578	0.1558	0.1549	0.1589	0.1573	0.1553	0.1545
BRT	0.1571	0.1553	0.1534	0.1521	0.1563	0.1547	0.1527	0.1513
OM	0.1589	0.1581	0.1561	0.1549	0.1602	0.1585	0.1565	0.1552
GRA	0.1615	0.1600	0.1579	0.1567	0.1610	0.1594	0.1575	0.1562
OF	0.1593	0.1577	0.1557	0.1546	0.1591	0.1576	0.1556	0.1545
TIM	0.1627	0.1611	0.1591	0.1578	0.1628	0.1614	0.1595	0.1581
ORM	0.1578	0.1561	0.1541	0.1530	0.1569	0.1551	0.1533	0.1523
FER	0.1626	0.1610	0.1590	0.1577	0.1629	0.1617	0.1597	0.1583
MM	0.1504	0.1486	0.1468	0.1454	0.1505	0.1486	0.1468	0.1455
PM	0.1600	0.1582	0.1562	0.1551	0.1608	0.1590	0.1570	0.1560

WN represents obtained estimated values from the conventional Westerlund and Narayan (2012, 2015) approach to estimating commodity prices predictability of stock prices, while WN_ASY represents the extended version denoting obtained estimates from our proposed asymmetric commodity prices predictability of stock prices. The smaller the RMSE value, the better the forecasting accuracy of a predictive model. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal.

Table 4
Forecast performance results for South Africa.

	WN predictive model				WN_ASY predictive model			
	In-sample RMSE	*Out-of-sample RMSE*			*In-sample RMSE*	*Out-of-sample RMSE*		
		h= 6	*h= 12*	*h= 18*		*h= 6*	*h= 12*	*h= 18*
Using 50% data sampled								
BEV	0.0559	0.0646	0.0634	0.0630	0.0556	0.0642	0.0630	0.0626
BRT	–	–	–	–	–	–	–	–
OM	0.0541	0.0623	0.0611	0.0607	0.0535	0.0610	0.0597	0.0596
GRA	0.0585	0.0678	0.0663	0.0661	0.0580	0.0670	0.0656	0.0655
OF	0.0577	0.0672	0.0658	0.0655	0.0578	0.0675	0.0661	0.0657
TIM	0.0595	0.0697	0.0683	0.0680	0.0593	0.0692	0.0678	0.0674
ORM* *	0.0557	0.0650	0.0640	0.0636	0.0557	0.0655	0.0643	0.0638
FER	0.0597	0.0696	0.0681	0.0678	0.0589	0.0690	0.0674	0.0668
MM	–	–	–	–	–	–	–	–
PM	0.0553	0.0639	0.0625	0.0633	0.0552	0.0639	0.0625	0.0633
Using 75% of the data sample								
BEV	0.0582	0.0579	0.0575	0.0585	0.0581	0.0578	0.0573	0.0584
BRT	–	–	–	–	–	–	–	–
OM	0.0565	0.0559	0.0555	0.0567	0.0549	0.0545	0.0540	0.0558
GRA	0.0613	0.0608	0.0603	0.0619	0.0610	0.0605	0.0600	0.0615
OF	0.0599	0.0594	0.0589	0.0604	0.0600	0.0595	0.0590	0.0605
TIM	0.0627	0.0623	0.0618	0.0635	0.0623	0.0619	0.0613	0.0630
ORM* *	0.0585	0.0580	0.0574	0.0588	0.0582	0.0578	0.0571	0.0585
FER	0.0638	0.0634	0.0629	0.0646	0.0627	0.0624	0.0619	0.0640
MM	–	–	–	–	–	–	–	–
PM	0.0581	0.0577	0.0571	0.0585	0.0579	0.0577	0.0570	0.0586

WN represents obtained estimated values from the conventional Westerlund and Narayan (2012, 2015) approach to estimating commodity prices predictability of stock prices, while WN_ASY represents the extended version denoting obtained estimates from our proposed asymmetric commodity prices predictability of stock prices. The smaller the RMSE value, the better the forecasting accuracy of a predictive model. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal.

Table 5
Results of Campbell –Thompson (C-T) test for Brazil.

	WN vs WN_ASY				WN vs WN_ASY			
	In-sample RMSE	*Out-of-sample RMSE*			*In-sample RMSE*	*Out-of-sample RMSE*		
		h= 6	*h= 12*	*h= 18*		*h= 6*	*h= 12*	*h= 18*
Using 50% data sampled					**Using 75% of the data sample**			
BEV	0.0006	0.0012	0.0014	0.0026	0.0017	0.0016	0.0014	0.0017
BRT	-0.0029	-0.0013	-0.0010	0.0007	-0.0008	-0.0005	-0.0021	-0.0022
OM	0.0023	0.0035	0.0029	0.0026	0.0073	0.0056	0.0074	0.0086
GRA	0.0013	-9.51E-05	-0.0002	-0.0007	0.0022	0.0022	0.0018	0.0013
OF	0.0082	0.0083	0.0041	0.0068	0.0052	0.0055	0.0041	0.0032
TIM	-0.0005	-0.0011	-0.0010	-0.0013	0.0013	0.0017	0.0002	0.0005
ORM	0.0036	0.0027	0.0026	0.0044	-0.0015	-0.0020	-0.0018	-0.0015
FER	-0.0040	-0.0046	-0.0047	-0.0064	0.0091	0.0087	0.0058	0.0039
MM	–	–	–	–	–	–	–	–
PM	-0.0009	-0.0007	-0.0008	-0.0007	-0.0047	-0.0045	-0.0051	-0.0062

The C-T test results are based on the forecast performance comparison of our preferred asymmetry version of WN predictive model against the conventional model. For the case of the conventional WN and the asymmetry version (WN_ASY), the former is treated as the restricted model and the latter unrestricted. A positive C-T value hypothetically indicates that the unrestricted model outperforms the restricted model, while a negative C-T value indicates otherwise. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal.

In order to validate the RMSE results, we additionally employ the Campbell and Thompson (2008) test. Conventionally, the C-T test is important in making a comparison between the predictive ability of the unrestricted and the restricted models (which in this case are the asymmetric commodity price-based model and the symmetric commodity price-based model respectively) premised on their RMSE values. Based on the C-T test results presented across Tables 5–7 for both the in-sample and the out-of-sample analyses, the results of the RMSE are consistently reaffirmed. In other words, in cases where the results based on the RMSE suggest that the

Table 6
Results of Campbell –Thompson (C-T) test for Russia.

	WN vs WN_ASY				WN vs WN_ASY			
	In-sample RMSE	*Out-of-sample RMSE*			*In-sample RMSE*	*Out-of-sample RMSE*		
		h= 6	*h= 12*	*h= 18*		*h= 6*	*h= 12*	*h= 18*
Using 50% data sampled					**Using 75% of the data sample**			
BEV	0.0104	0.0086	0.0080	0.0065	0.0030	0.0028	0.0030	0.0027
BRT	0.0080	0.0055	0.0040	-0.0005	0.0049	0.0044	0.0046	0.0051
OM	-0.0024	-0.0022	-0.0021	-0.0020	-0.0025	-0.0025	-0.0025	-0.0023
GRA	-0.0033	-0.0037	-0.0036	-0.0038	0.0035	0.0033	0.0030	0.0032
OF	-0.0074	-0.0070	-0.0070	-0.0066	0.0008	0.0006	0.0005	0.0005
TIM	-0.0022	-0.0019	-0.0022	-0.0028	-0.0005	-0.0019	-0.0023	-0.0018
ORM	0.0355	0.0332	0.0319	0.0279	0.0059	0.0065	0.0056	0.0050
FER	-0.0215	-0.0216	-0.0226	-0.0224	-0.0021	-0.0042	-0.0049	-0.0039
MM	0.0054	0.0041	0.0035	0.0016	-0.0003	-0.0004	-0.0004	-0.0005
PM	-0.0018	-0.0018	-0.0015	-0.0018	-0.0048	-0.0048	-0.0049	-0.0059

The C-T test results are based on the forecast performance comparison of our preferred asymmetry version of WN predictive model against the conventional model. For the case of the conventional WN and the asymmetry version (WN_ASY), the former is treated as the restricted model and the latter unrestricted. A positive C-T value hypothetically indicates that the unrestricted model outperforms the restricted model, while a negative C-T value indicates otherwise. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal.

Table 7
Results of Campbell –Thompson (C-T) test for South Africa.

	WN vs WN_ASY				WN vs WN_ASY			
	In-sample RMSE	*Out-of-sample RMSE*			*In-sample RMSE*	*Out-of-sample RMSE*		
		h= 6	*h= 12*	*h= 18*		*h= 6*	*h= 12*	*h= 18*
Using 50% data sampled					**Using 75% of the data sample**			
BEV	-0.0044	-0.0040	-0.0071	-0.0163	0.0018	0.0015	0.0027	0.0015
BRT	–	–	–	–	–	–	–	–
OM	0.0471	0.0450	0.0465	0.0314	0.0282	0.0249	0.0266	0.0157
GRA	0.0393	0.0388	0.0426	0.0447	0.0050	0.0058	0.0057	0.0060
OF	-0.0027	-0.0031	-0.0023	-0.0051	-0.0012	-0.0008	-0.0008	-0.0009
TIM	0.0243	0.0230	0.0247	0.0228	0.0060	0.0064	0.0069	0.0073
ORM	0.0588	0.0571	0.0533	0.0418	0.0052	0.0044	0.0056	0.0049
FER	0.0380	0.0342	0.0351	0.0428	0.0172	0.0165	0.0157	0.0097
MM	–	–	–	–	–	–	–	–
PM	-0.0018	-0.0020	-0.0025	-0.0002	0.0019	0.0010	0.0009	-0.0017

The C-T test results are based on the forecast performance comparison of our preferred asymmetry version of WN predictive model against the conventional model. For the case of the conventional WN and the asymmetry version (WN_ASY), the former is treated as the restricted model and the latter unrestricted. A positive C-T value hypothetically indicates that the unrestricted model outperforms the restricted model, while a negative C-T value indicates otherwise. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal.

asymmetric commodity price-based model or the symmetric commodity price-based model is the best, similar evidence is also provided by the C-T test. The relative exception relates to the prices of beverages and other raw materials in South Africa when 50% of the sample is used. Notwithstanding, the results are still consistent with the 75% sample.

6. Conclusion

It is evident that a continuous rise or fall in the stock market is perceptible to the changes in commodity prices. From the graphical analysis, we observe a strong co-movement between commodity prices and stock prices in BRICS countries, making us to preempt the possibility of commodity prices to predict and forecast stock prices. Therefore, we hypothesize that commodity prices are good predictors of stock prices in BRICS, rather than using the historical values of the latter, as indicated by traditional forecast models. Essentially, we employ the Westerlund and Narayan (2012, 2015) predictive model. The ability of this model to conveniently deal with certain statistical features of time series, such as conditional heteroscedasticity, serial dependence, persistence and endogeneity, among others, serves as an additional superiority over the traditional models.

Summarily, we find that only in India and China are commodity prices not suitable for predicting their stock prices irrespective of the sample used. Virtually all the ten commodity prices considered are found to be important predictors of stock prices in the remaining countries, except the price of minerals and metals for Brazil, and prices of crude oil and minerals and metals for South Africa. Then, since the global commodity market is often subject to significant volatilities, we further compare the best predictive model between the asymmetric commodity price-based predictive model and the symmetric commodity price-based predictive model using both RMSE and Campbell-Thompson (2008) test. The findings are mixed even though both tests largely produce similar evidence, indicating that some commodity prices predict stock prices asymmetrically while others do not in each country. We could then infer from the findings that the mixed evidence of symmetric and asymmetric forecast of stock prices in the three countries depend on the level of flexibility of the stock markets to shocks in each commodity market. Our results are not only consistent with both the in-sample and the out-of-sample forecasts, but also to different forecast horizons and alternative measure of forecast performance. Therefore, beyond understanding that commodity prices are viable predictors of stock prices in three of the BRICS countries by potential investors and policy makers, the role of asymmetries cannot be overemphasized in certain markets.

We further stress the need for future studies to consider the role of commodities in predicting the stock market performance of other countries with significance dependence on commodities. A good example is for many African studies which are known for significant dependence on primary commodities for foreign exchange earnings. Fluctuations in the prices of the commodities could affect their economies, consequently affecting the performance of their stock markets. It will also be more informative to test the predictive power of global commodity prices on several other financial indices such as green bonds, clean stocks, financial technology stocks, etc.

Appendix

See Tables A1 and B1.

Table A1
Preliminary Test Results.

Commodity Prices/ Countries		Descriptive statistics				Unit Root Test		Persistence and Endogeneity Tests	
		Mean	Standard Deviation	Skewness	Kurtosis	Level	First Difference	Persistence	Endogeneity
BEV	Brazil	72.1243	21.4866	0.1609	2.1419	-1.8887	-13.6731 * **	0.9862 * **	-0.3394
	Russia	72.2905	21.9485	0.1561	2.0770	-1.7689	-13.3013 * **	0.9918 * **	2.6974 * *
	India	72.1243	21.4866	0.1609	2.1419	-1.8887	-13.6731 * **	0.9862 * **	-0.1256
	China	85.9368	16.3054	-0.0749	2.8680	-1.5903	-9.1556 * **	0.9752 * **	0.3423
	South Africa	79.3360	20.7600	-0.1519	2.1856	-1.1979	-11.0417 * **	0.9806 * **	0.0009
BRT	Brazil	52.9667	33.72856	0.6122	2.1522	-2.0527	-14.0275 * **	0.9888 * **	-0.1630
	Russia	55.6104	33.4030	0.5336	2.0872	-1.9633	-13.5069 * **	0.9879 * **	-0.0456
	India	52.9667	33.72856	0.6122	2.1522	-2.0527	-14.0275 * **	0.9888 * **	-0.2111
	China	77.8546	25.7113	0.3168	1.8114	-2.7111	-8.6720 * **	0.9646 * **	0.4663
	South Africa	70.1343	29.0061	0.3178	1.9551	-2.1942	-10.5059 * **	0.9688 * **	-0.0796
OM	Brazil	76.64139	27.34186	0.5133	2.1323	-2.0955	-11.4852 * **	0.9912 * **	0.0192
	Russia	77.9961	27.8164	0.4003	2.0254	-2.2060	-10.8175 * **	0.9916 * **	1.8372 * *
	India	76.64139	27.34186	0.5133	2.1323	-2.0955	-11.4852 * **	0.9912 * **	-0.0463
	China	95.4711	22.6571	-0.1304	2.3056	-2.0443	-8.1842 * **	0.9724 * **	0.9412 * *
	South Africa	88.5905	25.7092	0.0405	1.9465	-1.9575	-8.8517 * **	0.9772 * **	0.0025
GRA	Brazil	81.54099	29.76143	0.8378	2.7545	-1.9372	-11.5035 * **	0.9925 * **	0.4210
	Russia	83.0119	30.2548	0.7361	2.5879	-2.0475	-11.2483 * **	0.9928 * **	1.2871
	India	81.54099	29.76143	0.8378	2.7545	-1.9372	-11.5035 * **	0.9925 * **	0.4788
	China	100.7353	26.5236	0.4855	2.1891	-2.1413	-8.8621 * **	0.9718 * **	0.5079
	South Africa	93.1296	29.3266	0.4987	2.2252	-1.5254	-9.6368 * **	0.9815 * **	0.12634
OF	Brazil	79.13916	20.40708	0.1898	1.4887	-2.1694	-15.9630 * **	0.9916 * **	0.3731
	Russia	80.3793	20.5772	0.0611	1.4700	-2.1532	-14.7053 * **	0.9923 * **	1.2380
	India	79.13916	20.40708	0.1898	1.4887	-2.1694	-15.9630 * **	0.9916 * **	-0.4010
	China	95.4809	12.2015	-0.5416	2.1413	-2.2444	-9.4927 * **	0.9674 * **	0.1214
	South Africa	89.7735	16.9478	-0.5552	2.1225	-1.9616	-11.1398 * **	0.9796 * **	-0.1453
TIM	Brazil	86.44710	17.12922	-0.2194	2.1541	-1.9238	-12.8610 * **	0.9914 * **	-1.1209
	Russia	85.7631	17.4506	-0.1355	2.0820	-1.8516	-12.6658 * **	0.9924 * **	-3.0044 * *
	India	86.44710	17.12922	-0.2194	2.1541	-1.9238	-12.8610 * **	0.9914 * **	-0.3379
	China	97.4132	10.4390	0.1808	2.7994	-2.1298	-10.1104 * **	0.9670 * **	-1.4074
	South Africa	92.2066	14.8826	-0.3322	2.4174	-1.0499	-11.4629 * **	0.9797 * **	-0.4998
ORM	Brazil	64.73434	21.96859	1.3701	5.7630	-2.1666	-10.6765 * **	0.9913 * **	0.0787
	Russia	65.4221	22.5262	1.2837	5.4211	-2.2177	-10.4073 * **	0.9936 * **	1.4238
	India	64.73434	21.96859	1.3701	5.7630	-2.1666	-10.6765 * **	0.9913 * **	0.2465
	China	78.7600	20.1095	1.6190	6.5352	-2.2896	-7.8819 * **	0.9695 * **	0.6630
	South Africa	73.1216	22.1155	1.2064	5.4179	-2.0284	-8.6734 * **	0.9790 * **	-0.1642
FER	Brazil	74.24167	43.98347	1.5794	6.3231	-1.9876	-9.6391 * **	0.9933 * **	0.6933
	Russia	76.6885	44.5319	1.5018	6.0774	-2.0159	-9.3775 * **	0.9954 * **	2.2915 * **
	India	74.24167	43.98347	1.5794	6.3231	-1.9876	-9.6391 * **	0.9933 * **	0.7967 *
	China	103.2972	40.5776	1.7730	7.0756	-2.3246	-6.2647 * **	0.9808 * **	1.1888 * **
	South Africa	92.8768	43.4774	1.4399	6.1638	-2.0649	-7.3446 * **	0.9810 * **	0.5653

(continued on next page)

Table A1 (*continued*)

Commodity Prices/ Countries		Descriptive statistics				Unit Root Test		Persistence and Endogeneity Tests	
		Mean	Standard Deviation	Skewness	Kurtosis	Level	First Difference	Persistence	Endogeneity
MM	Brazil	65.18021	28.00862	0.4317	1.8649	-2.0081	-11.4802 * **	0.9909 * **	-0.0008
	Russia	66.8362	28.2445	0.3225	1.7920	-1.9766	-10.9895 * **	0.9936 * **	0.5577
	India	65.18021	28.00862	0.4317	1.8649	-2.0081	-11.4802 * **	0.9909 * **	0.0722
	China	86.8653	19.1701	0.0675	2.2029	-3.2556 *	-8.0871 * **	0.9602 * **	-0.0324
	South Africa	79.1342	24.5389	-0.1524	2.1798	-2.2713	-8.9808 * **	0.9745 * **	0.0356
PM	Brazil	62.56738	38.59476	0.5677	1.9772	-1.3424	-14.8310 * **	0.9984 * **	0.8055
	Russia	56.6145	38.9332	0.4542	1.8819	-1.2630	-14.2794 * **	0.9980 * **	1.2030
	India	62.56738	38.59476	0.5677	1.9772	-1.3424	-14.8310 * **	0.9984 * **	0.2652
	China	91.8896	28.6849	-0.0007	2.4908	-1.4940	-10.9229 * **	0.9716 * **	0.1146
	South Africa	81.2716	34.9522	-0.0074	2.0419	-0.5545	-11.9810 * **	0.9867 * **	0.2603
STK	Brazil	42.73457	29.46200	0.6869	2.2838	-1.8413	-11.9028 * **		
	Russia	64.1253	46.3457	0.8033	2.7852	-2.2606	-10.5112 * **		
	India	64.7975	40.1397	0.3049	1.5773	-2.5660	-13.1327 * **		
	China	88.5432	26.2880	0.4120	3.7182	-2.9143	-6.5668 * **		
	South Africa	91.7956	30.6560	-0.8287	2.4548	-2.2531	-10.1499 * **		

* **, * * and * stand for 1%, 5% and 10% significance levels respectively. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal; STK = Stock.

Table B1
Preliminary Test Results.

Commodity Prices		Serial Correlation						Conditional Heteroscedasticity		
		Q-Stat			Q^2-Stat			ARCH LM		
		k = 6	k = 12	k = 18	k = 6	k = 12	k = 18	k = 6	k = 12	k = 18
BEV		1590.4 * **	2918.5 * **	4040.6 * **	1352.5 * **	1960.1 * **	2151.4 * **	821.02 * **	447.80 * **	278.74 * **
BRT		1629.1 * **	3010.2 * **	4187.2 * **	1237.9 * **	1754.8 * **	1896.9 * **	683.44 * **	355.32 * **	236.16 * **
OM		1636.5 * **	2987.8 * **	4158.0 * **	1189.9 * **	1652.5 * **	1916.8 * **	744.26 * **	368.36 * **	236.12 * **
GRA		1641.9 * **	2987.3 * **	4086.7 * **	1216.3 * **	1687.0 * **	1875.3 * **	913.98 * **	454.37 * **	304.66 * **
OF		1679.6 * **	3203.9 * **	4615.8 * **	1241.6 * **	1864.0 * **	2143.6 * **	392.34 * **	201.72 * **	133.63 * **
TIM		1642.8 * **	2916.5 * **	3862.4 * **	1193.2 * **	1527.3 * **	1545.2 * **	543.69 * **	289.42 * **	186.39 * **
ORM		1626.5 * **	2961.9 * **	4078.3 * **	1218.0 * **	1648.2 * **	1757.3 * **	1154.26 * **	586.17 * **	381.96 * **
FER		1664.4 * **	3033.8 * **	4167.7 * **	1101.4 * **	1248.1 * **	1251.9 * **	1414.79 * **	701.61 * **	457.89 * **
MM		1629.7 * **	2947.0 * **	4058.6 * **	1176.2 * **	1527.0 * **	1559.8 * **	648.40 * **	319.33 * **	204.02 * **
PM		1753.8 * **	3421.4 * **	4989.2 * **	1584.8 * **	2761.9 * **	3508.2 * **	1502.84 * **	741.77 * **	477.68 * **
STK	**Brazil**	1611.7 * **	2927.1 * **	3998.3 * **	1064.6 * **	1385.5 * **	1449.9 * **	549.33 * **	280.09 * **	191.78 * **
	Russia	1385.2 * **	2203.2 * **	2609.0 * **	1016.0 * **	1378.5 * **	1552.9 * **	453.28 * **	221.16 * **	142.66 * **
	India	1679.3 * **	3145.5 * **	4428.2 * **	1213.2 * **	1605.2 * **	1652.4 * **	683.41 * **	334.84 * **	223.40 * **
	China	622.67 * **	721.50 * **	739.23 * **	405.32 * **	486.42 * **	541.27 * **	102.17 * **	107.92 * **	38.16 * **
	South Africa	954.68 * **	1533.9 * **	1859.3 * **	849.94	1233.5	1341.2 * **	1754.86 * **	465.63 * **	107.10 * **

* ** stands for 1% significance level. BEV = Beverages, BRT = Crude oil, OM = oil and meals, FER = Fertilizer, GRA = Grains, MM = Metal and mineral; OF = Other food; TIM = Timber; ORM = Other raw material; PM = Precious metal; STK = Stock.

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