Oil Price and Exchange Rate Behaviour of the BRICS for Over a Century

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Abstract

We attempt to predict the exchange rate returns of BRICS countries with the global oil price using large historical datasets for over a century extending from September 1859 to April 2020. We formulate a predictive model that accounts for the salient features of the predictor and the predicted series in line with the recent literature. We establish, with the aid of asymmetry, that oil price is a good predictor of exchange rate returns for all the net oil-importers (India, South Africa and China) and one of the two net oil-exporters (Russia). We also demonstrate with compelling in-sample and out-of-sample forecast results that accounting for the role of asymmetry is crucial for the oil-based model to beat the benchmark (historical average) model.

Keywords: Oil price, Exchange rate return, BRICS, Asymmetry, Predictability, Forecast evaluation.

JEL Codes: C22, C53, F31, Q47.

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1. Introduction

Since 2001, when Jim O'Neill coined the acronym BRIC for Brazil, Russia, India, and China, this group of countries has experienced spectacular growth rates, and has played an increasingly important role in the world economy[1]. BRICS nations represent 42% of the total global population and 23% of total global GDP (IMF, 2019). Furthermore, the relevance of BRICS countries in both the generation and consumption of energy is undeniable. According to the International Energy Agency (IEA, 2019), BRICS countries account for 36.4 percent primary energy supply and this is set to rise to 40–50 percent by 2040. In fact, BRICS countries include both the largest and fastest-growing energy producers and consumers in the world. Russia is the world's number 2 net exporter of crude oil, while China and India stand as the world's first and third net crude oil importers. At the same time, BRICS countries' exchange rates, unlike exchange rates in developed countries, have not been allowed to float freely, but they have been strictly controlled by different currency policies (Jiang, 2019) until recently. For example, China fixed its exchange rate in 1995 to the US dollar and maintained that peg until July 2005, while the ruble has been trading freely since 2014, when Russia abandoned a previous peg. At the same time, the exchange rate system in India has transited from a fixed exchange rate regime to the present form of freely determined exchange rate regime since 1993, while Brazil and South Africa adopted a floating exchange rate regime in 1999 and 2000, respectively. The differences in oil dependence among BRIC countries and their diverse exchange rate regimes or currency interventions make the analysis of the interaction between oil prices and exchange rates in BRICS countries very relevant, not only for investment and risk management but also for the economic and financial stability (Turhan et al., 2014).

The literature has widely analyzed the impact of oil prices on macroeconomic variables, (Hamilton, 1983, 2003; 2008; 2009; 2011; Kilian, 2018) such as per capita GDP growth rates and inflation rates (Hamilton, 1983, 1988; Mork, 1989; Hooker, 1996; Cunado and Perez de Gracia, 2003; 2005), stock returns (Jones and Kaul, 1996; Narayan and Gupta, 2015; Salisu and Oloko, 2015; Salisu and Isah, 2017; Salisu et al., 2019a), and exchange rates (Amano and von Norden, 1998; Chen and Chen, 2007; Wu et al., 2012; Narayan, 2013; Salisu and Mobolaji, 2013; Ji et al., 2019). From a theoretical point of view, different direct transmission channels from oil prices to exchange rates can be considered. First, according to the terms of trade channel (Amano and van Norden, 1998; Bénassy-Quéré et al., 2007), an oil price increase will be followed by a depreciation

[1] South Africa joined this group of countries in 2010 and formed the BRICS.

of those currencies in countries with large oil dependence in the tradable sector since the price level in this country will increase. Second, in line with the wealth and portfolio channels (Krugman, 1983; Golub, 1983; Turhan et al., 2014; Buetzer et al., 2016), when oil prices rise, wealth is transferred to oil-exporting countries and this is reflected in an improvement in the current account balance, so that oil-exporting countries' currencies are expected to appreciate while currencies of oil-importers are expected to depreciate after an oil price increase. Furthermore, exchange rate movements can also be transmitted to oil prices. For example, an appreciation of the US dollar increases the price of oil measured in terms of the domestic currency of an oil-importing economy, which leads to a decrease in the demand for oil outside the US, resulting in a drop of the oil price (Bloomberg and Harris, 1995; Akram, 2009).

The empirical literature has also extensively examined the oil prices and exchange rate dynamics (Amano and von Norden, 1998; Chen and Chen, 2007; Wu et al., 2012; Narayan, 2013), although the results are not conclusive. For example, while some studies find that oil prices Granger cause exchange rate movements (Benhmad, 2012; Chen and Chen, 2007; Lizardo and Mollick, 2010; Tiwari et al., 2013), there is also evidence of unidirectional relationship running from exchange rate movements to oil price changes (Reboredo, 2012) while a bidirectional relationship is also reported in the study of Salisu and Mobolaji (2013). In other words, the probable causal relationship between the two variables has been widely studied. However, the analysis of the predictive power of oil prices to forecast exchange rates has been barely explored (Chen and Chen, 2007; Chen et al., 2010; Ferraro et al., 2015). Chen and Chen (2007) study the long-run relationship between real oil prices and exchange rates for G7 countries, they find that real oil prices have significant forecasting power and they obtain that out-of-sample prediction performances improve over longer horizons. On the other hand, Chen et al. (2010) find that while commodity prices Granger cause exchange rates in-sample, this relationship is not robust to out-of-sample while the contrary is obtained in the study of Salisu et al. (2019b). Ferraro et al. (2015) analyse the out-of-sample relationship of oil prices with the Canadian/US dollar exchange rate obtaining little systematic relation between these two variables at the monthly and quarterly frequencies.

In this context, the objective of this paper is to predict the exchange rate returns of BRICS countries based on oil prices using data for over a century ranging from September 1859 to April 2020. This paper contributes to the literature on exchange rates predictability in several ways. First, we analyse each of the BRICS economies separately, allowing for heterogeneity in the response of exchange rates to oil price movements. Since each of the BRICS countries has chosen different exchange rate regimes or currency interventions, the response of exchange rates to oil price movements could be different (Huang and Guo, 2007; Huang et al., 2020). Furthermore, the different degree of oil dependence in each of the BRICS countries will also determine the response of exchange rates to oil price changes. Second, the paper considers both in-sample and out-of-sample forecast evaluation, while most of literature only consider in-sample forecasts. Since in-sample predictability may not necessarily translate into improved out-of-sample forecast, extending forecast analyses to capture the latter is crucial particularly for policy decisions. Third, this paper contemplates the possibility of asymmetric responses of exchange rates to oil prices, allowing that exchange rates might react more to oil price increases than to decreases (Atems et al., 2015; Salisu et al., 2019b; Baek and Choi, 2020). Finally, the analysis covers an ample period of more than a hundred years, in which oil prices have suffered great fluctuations and exchange rates of BRICS countries have also experienced different regimes. Up to our knowledge, this is the first paper which try to analyse the predictive power of oil prices forecasting exchange rates of BRICS countries using a large historical dataset which cover more than a hundred years.

The main results suggest that oil prices are a good predictor of exchange rate returns, both when in-sample and out-of-sample forecasts are considered. Furthermore, exchange rates respond differently to oil price increases and decreases, suggesting that the role of asymmetry is crucial for the prediction model. Finally, the results indicate that oil prices are a good predictor of exchange rate returns in India, South Africa, China and Russia, but not in the case of Brazil.

The remainder of the paper is structured, as follows. Section 2 describes the data and the preliminary analysis. Section 3 provides the model and the estimation procedure. Section 4 presents the empirical results, and finally, Section 5 contains some concluding remarks.

2. Data and Preliminary Analyses

The variables of interest in this study are historical monthly exchange rates for BRICS [Brazil, Russia, India, China and South Africa] countries and the global oil price, covering the period from September 1859 to April 2020. Both exchange rate and oil price data are obtained from Global Financial Data.[2] The start date for China is adjusted to August 1948 to align with its exchange rate

[2] http://www.globalfinancialdata.com/.

data. The predicted series (i.e. exchange rate) is expressed in returns due to the expected investment undertone of the study. The exchange rate return is measured as the log return of the domestic currency of each of the BRICS countries with respect to USD, the reference currency while the West Texas Intermediate (WTI) in USD is used as a proxy for oil price. [3] In this section, we offer some descriptive statistics as well formal tests required for the choice of methodology adopted in this study.

The results of the descriptive statistics are presented in Table 1, showing the mean, standard deviation, skewness, and kurtosis. We observe that all the exchange rate have experienced depreciation on average over the period under consideration with Brazil recording the highest depreciation followed by Russia while South Africa seems to have the strongest currency, on average. The inference from the standard deviation values somewhat follows that of the mean statistics as Russia's currency is the most volatile followed by Brazil, while South Africa is the least volatile. Nonetheless, all the currency series are positively skewed and leptokurtic. Worthy of note, however, is the fact that the descriptive statistics for the oil price variable remain the same for all the BRICS countries since crude oil is a globally traded commodity and it is found to be more volatile but less skewed and less leptokurtic than any of the return series for the BRICS exchange rates.

[3] Unlike exchange rate that is measured in return form in all the analyses rendered in this study, the oil price is expressed in level form for the summary statistics but expressed in natural logs for the formal tests and empirical analyses. Oil price is not expressed in return form to avoid "double" differencing of the series as its log return is already incorporated in the model by design of the adopted methodology. This log return of oil price is not the predictor rather it is included in the model to deal with endogeneity and persistence issues. This is discussed in the methodology section.

Table 1: Descriptive Statistics and Unit Root Test

Variable		Mean	Standard Deviation	Skewness	Kurtosis	ADF		
						Level	FD	I(d)
Exchange Rate return	Brazil	0.0190	0.0701	3.2270	22.3654	-9.15^{b***}	-	I(0)
	Russia	0.0140	0.1235	11.8407	222.052	-18.91^{b***}	-	I(0)
	India	0.0019	0.0325	11.0625	274.292	-19.98^{b***}	-	I(0)
	China	0.0076	0.0640	11.6715	166.809	-7.25^{b***}	-	I(0)
	S-Africa	0.0020	0.0285	1.8606	37.5196	-35.79^{b***}	-	I(0)
Oil Price		12.9923	22.0010	2.5603	9.51	-4.8462	-28.49^{b***}	I(1)

Note: ADF test is the Augmented Dickey Fuller test; FD denotes First Difference; ***, **, & * indicate the rejection of the null hypothesis of a unit root at 1%, 5% and 10%, respectively; the test regression for all the unit root tests includes intercept and trend; I(d) implies the order of integration, where d is the number of differencing required for a series to become stationary.

Table 2: Preliminary tests

Table 2(a): Serial Correlation and Conditional Heteroscedasticity Tests

		$Q-Stat$			Q^2-Stat			ARCH LM Test		
		$k=2$	$k=5$	$k=10$	$k=2$	$k=5$	$k=10$	$k=2$	$k=5$	$k=10$
Exchange rate returns	Brazil	924.51***	1885.2***	3207.3***	364.21***	597.49***	838.40***	159.8***	72.4***	38.40***
	Russia	173.51***	256.45***	325.10***	56.89***	62.247***	64.32***	27.06***	11.27***	5.70***
	India	36.09***	65.31***	69.41***	16.35***	44.36***	44.60***	7.89***	8.71***	4.45***
	China	476.35***	974.23***	1156.5***	139.48***	139.48***	336.52***	71.31***	49.71***	520.95***
	S-Africa	86.92***	100.37***	114.22***	23.05***	70.85***	170.96***	10.82***	11.02***	11.94***
Oil Price		3824.2	9414.0***	18325.***	3735.9***	8796.8***	16037.***	67467.***	27752.***	14001.***

Table 2(b): Testing for Endogeneity and Persistence of the Predictor (Oil Price)

	Brazil	Russia	India	China	S-Africa
Persistence test results	0.9977***	0.9977***	0.9973***	0.9977***	0.9977***
	(0.0015)	(0.0015)	(0.0015)	(0.0019)	(0.0015)
Endogeneity test results	-0.0160	-0.0418	-0.0024	-0.0290	-0.0298**
	(0.0171)	(0.0308)	(0.0081)	(0.0320)	(0.0070)

Note: The reported values for the Ljung-Box test are the Q- and Q^2 statistics and F-statistic for ARCH-LM test. Three different lag lengths (k); 2, 5 and 10 are considered for robustness purpose. The persistence test is conducted by regressing each of the predictors on its first lag using OLS estimator. For the endogeneity test, it follows a three-step procedure: First, we run a predictive regression model with the OLS estimator: $r_t = \alpha + \lambda z_{t-1} + \varepsilon_{r,t}$, where r_t denotes exchange rate returns and z_{t-1} is the lag of the predictor variable. In the second step, we follow WN (2015) and model the predictor variable as follows: $z_t = \mu(1-\delta) + \delta z_{t-1} + \varepsilon_{z,t}$ and in the final step, the relationship between the two error terms ($\varepsilon_{r,t}$ and $\varepsilon_{z,t}$) is captured using the following regression: $\varepsilon_{r,t} = \rho\varepsilon_{z,t} + \eta_t$. If the coefficient ρ is statistically different from zero; then, the predictor variable is endogenous; otherwise, it is strictly exogenous. ***, ** implies 1% & 5% level of significance, respectively.

Equally, the Augmented Dickey Fuller test results showing the stochastic property of the series are reported in Table 1. These show that the exchange rate returns series are stationary irrespective of the country under investigation. However, log of oil price, the predictor series, is shown to exhibit non-stationarity property. The outcome is not surprising for the two series, the exchange rate returns are in first difference form and technically this should be stationary, however, the logged oil price is still in level form which explains why it is only stationary after first difference. Quite interesting in this regard is the fact that the stochastic behaviour of both the predicted and predictor series aligns with the requirements for the chosen methodology. In order to allow for other salient effects typical of most economic and financial series, we further test for the presence of autocorrelation (using the Ljung-Box test) and conditional heteroscedasticity (using the ARCH-LM test) in both the predicted and predictor series (see Table 2).

As expected of historical and high frequency data, the outcome of the foregoing tests report significant evidence of autocorrelation and heteroscedasticity regardless of the choice of lags. We also find evidence of high degree of persistence in the predictor and this is not unexpected for series that is integrated of a higher order (other than zero). There is however limited evidence for endogeneity bias as presented. Thus, since it has been argued that ignoring these highlighted effects can undermine the potential of a predictor in predicting return series, the modelling in the immediate section is constructed to reflect these underlying features in the oil-exchange rate predictive model (see Westerlund & Narayan, 2012, 2015)[4].

3. The Model and Estimation Procedure

3.1 The model

Sequel to the outcomes of our preliminary analyses, we formulate in equation (1) a bivariate predictive model for the oil-exchange rate nexus in a way that allows for some salient features of the series. Essentially, we control for endogeneity so as to circumvent the potential bias that could arise from the omission of other predictors of exchange rate returns. We also control for conditional heteroscedasticity in the specification due to both the historical and high frequency nature of the series. Another common feature of financial series also controlled for is the

[4] Recent applications of this methodology, particularly those related to returns, include but not limited to Bannigidadmath & Narayan (2015), Narayan & Bannigidadmath (2015), Narayan & Gupta, (2015), Phan, Sharma, & Narayan (2015),Narayan, Phan, Sharma, Westerlund (2016); Devpura, Narayan, & Sharma (2018); Salisu et al. (2019a&b).

persistence effect in the predictor series. Following the Westerlund and Narayan [WN hereafter] (2012, 2015), our exchange rate predictive model is specified as:

$$er_t = \alpha + \sum_{i=1}^{5} \lambda_i^{adj} op_{t-i} + \gamma \left(op_t - \delta_0 op_{t-1} \right) + \eta_t \qquad (1)$$

where er_t denotes exchange rate returns computed as log return of exchange rates of BRICS member countries with USD as the reference currency, op is the log of oil price (using West Texas Intermediate crude oil price as a proxy). The term η_t captures zero mean idiosyncratic error term while λ_i^{adj} is the coefficient that measures the relative impact of oil price on exchange rate returns. The null hypothesis of no predictability is considered via a joint (Wald) test using lag 5, symbolically represented as: $\sum_{i=1}^{5} \lambda_i^{adj} = 0$. Worthy of note however is the fact that the model depicted in equation (1) originates from the following specification:

$$er_t = \alpha + \lambda op_{t-1} + \varepsilon_t \qquad (2)$$

Equation (2) is the reduced form of equation (1) and suppressing the oil price term - λop_{t-1} further reduces the model to Historical Average - $er_t = \alpha + \varepsilon_t$. The parameter λ^{adj} which is particularly derived as $\lambda^{adj} = \lambda - \gamma\left(1-\delta_0\right)$ (where δ_0 is the measure for the degree of persistence in the predictor series op_t) corrects for any persistence effect including any inherent unit root problem in the predictor series (see Lewellen, 2004). Also, the term $\gamma\left(op_t - \delta_0 op_{t-1}\right)$ which is another extension to the conventional OLS estimator, corrects for any inherent endogeneity bias resulting from the correlation between op_t and ε_t. In addition, we control for conditional heteroscedasticity effect given the nature of our data frequency by pre-weighting all the data with $1/\hat{\sigma}_\eta$ and estimating the resulting equation with the Ordinary Least Squares (OLS) (see WN, 2012, 2015, for computational details). The modified OLS in this regard is referred to as the Feasible Quasi GLS estimator in WN (2012, 2015) and it is technically computed as:

$$\lambda_{adj}^{FQGLS} = \frac{\sum_{t=q_m+2}^{T} \tau_t^2 er_{t-1}^d op_t^d}{\sqrt{\sum_{t=q_m+2}^{T} \tau_t^2 \left(op_{t-1}^d\right)^2}} \qquad (3)$$

where $\tau_t = 1/\sigma_{\eta,t}$ is used in weighting all the data in equation (3) and $op_t^d = op_t - \sum_{s=2}^{T} op_t / T$.[5]

3.2 Forecast performance evaluation procedure

We further test whether compared to the conventional approach to forecasting financial and economic series, that is, the Historical Average (HA), accounting for the inherent features of the predictor and the predictive model will produce better forecast results. However, the fact that the HA is a restricted version of the specification in equation (1) suggests that the two models are nested. For the purpose of robustness, both the single and pairwise forecast performance measures are used. The former in this case is the Mean Square Error (MSE) which does not take note of the nested nature of the two models. Hence, the MSE is complemented with the Campbell & Thompson (2008) [C-T hereafter] test. Mathematically, the single forecast–based measure is represented as: (MSE) - $1/N \sum_{t=1}^{T} (\hat{er}_t - er_t)^2$ where N is number of predictions used in computing the mean with $\hat{er}_t$ and er_t denoting the fitted and actual values of exchange rate returns, respectively.

With respect to the pairwise forecast measure, the C-T test is computed as $1-\left(M\hat{S}E_1 / M\hat{S}E_0\right)$, where $M\hat{S}E_1$ and $M\hat{S}E_0$ are the mean square errors (*MSE*) of the unrestricted model and restricted model, respectively. A positive value of the statistic is an indication that the unrestricted model, the model in equation (1) outperforms the restricted model (i.e. HA) and vice-versa, if otherwise. While acknowledging the adequacy of C-T test for evaluating the forecast performance of nested model, we yet complement the procedure with Clark and West (2007) test. The underlying procedure for the Clark and West [henceforth C-W] (2007) test involves calculating the following:

[5] See Westerlund and Narayan (2012, 2015) for computational details.

$$\hat{f}_{t+k} = \left(er_{t+j} - e\hat{r}_{1t,t+j}\right)^2 - \left[\left(er_{t+j} - e\hat{r}_{2t,t+j}\right)^2 - \left(e\hat{r}_{1t,t+j} - e\hat{r}_{2t,t+j}\right)^2\right] \quad (4)$$

where j is the forecast period; $\left(er_{t+j} - e\hat{r}_{1t,t+j}\right)^2$ is the squared error for the restricted model while $\left(er_{t+j} - e\hat{r}_{2t,t+j}\right)^2$ is the squared error for the unrestricted model. The term $\left(e\hat{r}_{1t,t+j} - e\hat{r}_{2t,t+j}\right)^2$ is the adjusted squared error introduced by C-W to correct for any noise associated with the larger model's forecast. Thus, the sample average of $\hat{f}_{t+k}$ can be expressed as: $MSE_0 - \left(MSE_1 - \text{adj.}\right)$ and each term is computed as:

$$MSE_0 = N^{-1}\sum\left(er_{t+j} - e\hat{r}_{1t,t+j}\right)^2;$$

$$MSE_1 = N^{-1}\sum\left(er_{t+j} - e\hat{r}_{2t,t+j}\right)^2; \text{ and}$$

$$\text{adj.}=N^{-1}\sum\left(e\hat{r}_{1t,t+j} - e\hat{r}_{2t,t+j}\right)^2$$

To test for equality of forecast performances between the restricted and unrestricted models, the $\hat{f}_{t+k}$ term is regressed on a constant and the resulting t-statistic for a zero coefficient is used to draw inference. Since the null hypothesis tests for equality of MSEs; the alternative hypothesis implies otherwise such that the null hypothesis is rejected if the test statistics is greater than +1.282 (for a one-sided 0.10 test) and/or +1.645 (for a one-sided 0.05 test). The rejection of the null hypothesis in the context of this study implies that the predictive model in equation 1 is the most appropriate for the predictability of exchange rate returns. With the rich historical data at our disposal, we use 50% of the observations for both the in-sample and out-of-sample forecasts. Since the data is monthly frequency, we consider 4-month, 8-month and 12-month ahead forecast horizons using the recursive approach to forecasting.

4. Discussion of results

We present the in-sample predictability results in Table 3 showing the ability of oil price to predict exchange rate returns of the BRICS. While we generally expect to obtain significant estimates across the BRICS countries, however, we may not expect uniform direction of relationships in terms of sign. The relationship between the two variables of interest usually depends on the peculiarity of the economy under investigation. First, the monetary policy authorities often tailor the country's exchange rate framework along the monetary policy targets that favour the economy in question. Second, oil price changes have been shown to affect economies differently based on the nature of the shock and whether the economy in question participates more in the demand-side or the supply-side of the global oil market (see Salisu & Isah, 2017 for elaborations). Thus, it is expected that for oil exporting BRICS countries such as Brazil and Russia, the exchange rate should appreciate in response to rising oil prices, while the reverse is expected to be the case for the rest of the BRICS countries given their net oil–importing status.

Given the rejection of the null hypothesis of no predictability (with Brazil and India as the exceptions), we report (in Table 3) that oil price can only predict exchange rate returns in three out of the five BRICS countries (i.e. Russia, China and South Africa) using the linear (symmetric) predictive model. There are mixed signs as previously alluded indicating that the relationship depends on the nature of the economy in question (see also, Lizardo and Mollick, 2010 for previous, although limited findings for the differential impact of oil price on currency pairs). Moreover, the economic intuition of the likelihood of a positive shock to oil price resulting in appreciation of exchange rate in net oil-exporting countries appears to hold significantly for Russia and for China among net oil-importers. Chaudhuri and Daniel (1998), Huang and Guo (2007), and Benassy-Quere et al. (2007), among others, are some of the earlier studies that also lend credence to the potential of oil price in improving exchange rate behaviour. Unlike our paper, the previous studies do not seem to pay attention to the distinct features of the economy in question in their analyses and neither do they rely on such large dataset for evidence, as demonstrated in our study.

Still on Table 3, the inclusion of positive and negative partial sums for oil price (i.e. incorporating asymmetry) appears to strengthen the predictive role of oil price for the BRICS' exchange rates particularly for Russia, India, China and South Africa. Notwithstanding the consideration of asymmetry, the null of no predictability still remains unyielding for Brazil. However, given the evidence in four out of five cases, it is safe to carry on with the forecast evaluation of the oil-based predictive model for exchange rate. Thus, Brazil is inevitably suppressed from the BRICS countries considered for the in-sample and out-of-sample forecast performance evaluation in the immediate sub-section.

Table 3: Predictability test results

	Brazil	Russia	India	China	S-Africa
op_t	-0.0016	0.0305***	-0.0006	0.0094***	-0.0020***
	(0.0022)	(0.0006)	(0.0010)	(0.0005)	(0.0001)
op_t^+	-0.0014	0.0206***	0.0019**	-0.0010***	0.0012***
	(0.023)	(0.0008)	(0.0008)	(0.0001)	(0.0001)
op_t^-	-0.0014	0.0185***	0.0025***	0.0500***	0.0005***
	(0.0023)	(0.0007)	(0.0007)	(0.0017)	(0.0001)

Note: Values in parentheses ( ) denote standard errors, while ***, ** and * denote levels of significance at 1%, 5% and 10%, respectively.

4.1 Forecast performance evaluation

Beyond the in-sample predictability test results in Table 3, we further subject the estimated predictive model(s) to both in-sample and out-of-sample forecast performance evaluation. Essentially, we explore both the single (MSE) and pairwise (C-T & C-W) tests to determine in relative terms, the predictive power of oil price in exchange rate, compared to the conventional time-series approach to forecasting, that is, the HA model. Starting with the single-measure forecast performance, the MSE values reported in Table 4(a) seem reasonably low for both the oil–based predictive model (say Model 1 for convenience) and HA predictive model (say Model 2). Nonetheless, the MSE values seem relatively lower for Model 1 compared to Model 2 when the exchange rate is Russian ruble, while the reverse appears to be the rest of the BRICS countries for instance the Indian rupee, the Chinese yen and the South Africa Rand. This evidence seems robust across both the in-sample and out-of-sample forecasts.

In addition, a cursory look at the (b) part of Table 4 shows overwhelming negative C-T values, which hypothetically suggest that compared to Model 1, the HA predictive model (Model 2) appears as a better model particularly for India, China and South Africa. To ascertain the significance or otherwise of this C-T test results and by extension the MSE values, the C-W test is employed. The underlying intuition is to determine whether the difference between the forecast errors of the two nested models (Model 1 and Model 2) is statistically significant. A non-rejection of the null of the C-W test implies identical forecast accuracy between the two models while a rejection favours Model 1. We find that the earlier inference that Model 2 outperforms Model 1 in three of the BRICS countries under consideration appears to be statistically viable but only in South Africa. Interestingly, previous studies such as Moosa (2013), Moosa & Burns (2012, 2014a,b,&c), among others, have also cast doubts on the potential of economic models in outperforming time series models when forecasting exchange rate.

This conclusion further motivates our interest to investigate the role of asymmetry in the nexus given recent findings in the literature (see for example, Narayan and Gupta, 2015; Salisu, et al., 2019b) which suggest that accounting for asymmetry in the predictor series may improve its forecast performance.

Table 4(a): Forecast performance results using MSE

	Model 1				Model 2			
		Out-of-sample				Out-of-sample		
BRICS	**In-sample**	***h=4***	***h=8***	***h=12***	**In-sample**	***h=4***	***h=8***	***h=12***
Russia	0.01760	0.01749	0.01742	0.01735	0.01780	0.01769	0.01762	0.01755
India	0.00159	0.00158	0.00157	0.00156	0.00157	0.00156	0.00156	0.00155
China	0.00797	0.00797	0.00786	0.00783	0.00771	0.00764	0.00758	0.00752
S-Africa	0.00079	0.00083	0.00083	0.00083	0.00071	0.00076	0.00076	0.00076

Table 4(b): Pairwise forecast performance results for Model 1 vs Model 2

	C-T test				C-W test			
		Out-of-sample				Out-of-sample		
BRICS	**In-sample**	***h=4***	***h=8***	***h=12***	**In-sample**	***h=4***	***h=8***	***h=12***
Russia	0.011	0.011	0.011	0.011	3.470***	3.459***	3.459***	3.455***
India	-0.007	-0.008	-0.007	-0.007	-0.940	-0.935	-0.923	-0.922
China	-0.033	-0.043	-0.038	-0.041	0.269	0.231	0.039	-0.225
S-Africa	-0.108	-0.099	-0.097	-0.097	-1.719***	-1.583***	-1.520***	-1.519***

Note: The C-T test results are based on the forecast performance comparison of the oil-based model (described as Model 1) and the historical average model (denoted as Model 2). Hypothetically, a positive C-T value implies that Model 1 outperforms Model 2 and the reverse holds if the statistic is negative. For the C-W test, the t-statistics reported are based on the critical values of 1.28, 1.65 & 1.96 for 10% (*) and 5% (**) & 1%(***) levels of significance, respectively.

4.2 Does asymmetry matter in oil price predictability of exchange rate returns?

As noted previously, we test whether accounting for nonlinearity in form of asymmetry effect in oil price will improve the predictability as well as forecast performance of the oil-based model. For a detail description of the decomposition of oil price into positive and negative changes, see Shin et al. (2014)[6]. Recall the asymmetry result is earlier presented and included in Table 1. The ensuing extended predictive model from which the results are obtained is specified in equation (5).

$$er_t = \alpha + \sum_{i=1}^{5} \lambda_i^{+adj} op_{t-i}^{+} + \sum_{i=1}^{5} \lambda_i^{-adj} op_{t-i}^{-} + \gamma^{+}\left(op_t^{+} - \delta_0^{+} op_{t-1}^{+}\right) + \gamma^{-}\left(op_t^{-} - \delta_0^{-} op_{t-1}^{-}\right) + \varepsilon_{er,t} \quad (5)$$

[6] This approach has continued to gain prominence in the literature and some of its computational advantages are rendered in Shin et al. (2014).

where $op_t^+ = \sum_{k=1}^{t} \Delta op_{ik}^+ = \sum_{k=1}^{t} \max(\Delta op_{ik}, 0)$ and $op_t^- = \sum_{k=1}^{t} \Delta op_{ik}^- = \sum_{k=1}^{t} \min(\Delta op_{ik}, 0)$ and there is presence of asymmetric effect if the coefficients on op_t^+ and op_t^- are statistically different, otherwise, the effects of both are considered symmetric. For robust comparison and to ensure consistency, the asymmetric model is denoted as Model 3 and its in-sample and out-of-sample forecast results are compared with those obtained from Model 2 which can now be regarded as a restricted version of Model 3. The C-T and C-W test statistics presented in Table 4 confirm our hypothesis that oil price asymmetry seems to matter in the forecasting power of oil price in exchange rate predictability. For instance, the C-T test statistics are predominantly positive for all the BRICS countries thus implying that accounting for the role of asymmetries is crucial for enhancing oil price predictability for exchange rate. This outcome aligns well with the studies of Atems et al. (2015), Salisu et al. (2019b), and Baek and Choi (2020) which attest to the asymmetric response of exchange rate to oil price changes. Not only is this finding robust across the in-sample and out-of-sample forecasts, the significance of the finding is evident and statistically confirmed by the C-W test results.

Table 5: Pairwise forecast performance results for Model 3 vs Model 1

BRICS	C-T test				C-W test			
		Out-of-sample				Out-of-sample		
	In-sample	***h=4***	***h=8***	***h=12***	**In-sample**	***h=4***	***h=8***	***h=12***
Russia	0.00999	0.00962	0.00937	0.00914	3.5473***	3.5121***	3.4933***	3.4730***
India	0.00325	0.00315	0.00308	0.00287	2.9269***	2.9305***	2.9308***	2.9329***
China	0.01467	0.02390	0.01056	0.00712	3.4391***	3.3581***	0.3933	-0.9584
S-Africa	0.07929	0.07027	0.06734	0.06704	6.3807***	5.9252***	5.8562***	5.8529***

Note: The C-T test results are based on the forecast performance comparison of Model 1 and Model 3. Hypothetically, a positive C-T value implies that Model 3 outperforms Model 1 and the reverse holds if the statistic is negative. For the C-W test, the t-statistics reported are based on the critical values of 1.28, 1.65 & 1.96 for 10% (*) and 5% (**) & 1%(***) levels of significance, respectively.

5. Concluding remarks

The study adopts large historical datasets extending from September 1859 to April 2020 to undertake the predictability of BRICS countries' exchange rates with the global oil price. The relevance of BRICS countries in both the generation and consumption of energy, and the episodes of currency manipulation observed in some currencies, make this objective of great importance. Based on the literature, we would expect to obtain different responses of exchange rates to oil price movements depending on whether the analyzed country is an oil-importing (India, China, South Africa) or oil-exporting (Brazil, Russia), and on the degree of currency interventions carried out during this long period by each of the countries. The predictive models explored are the symmetric (linear) model and asymmetric (nonlinear) model that incorporates the positive and negative oil price changes as well as historical average. The oil-based models take account of endogeneity bias due to possible correlation between the predictor and the error term, conditional heteroscedasticity in the series due to historical and high frequency nature of the series, and the identified persistence effect in the predictor series. We find evidence of in-sample predictability of oil price for exchange rates of three of the five BRICS countries when the linear model is considered and the predictability improves after accounting for asymmetry effect, suggesting that exchange rates react more pronouncedly to oil price increase than to oil price decreases. We further show that the role of asymmetry effect in the oil-exchange rate nexus extends to both the in-sample and out-of-sample forecast performance of the oil-based model and ignoring this effect may upturn the results in favour of the historical average. Given the severe adverse effects of the current pandemic [COVID-19] on the global economy with attendant implications on oil price, future studies that examine the behaviour of oil-exchange rate nexus during pandemics would enrich the literature and further broaden our understanding of the nexus particularly during turbulent periods.

References

Amano, R.A., van Norden, S., 1998. Oil prices and the rise and fall of the US real exchange rate. Journal of International Money and Finance 17, 299-316.

Atems, B., Kapper, D., Lam, E., 2015. Do exchange rates respond asymmetrically to shocks in the crude oil market? Energy Economics 49, 227-238.

Baek, J., Choi, Y.J., 2020. Do fluctuations in crude oil prices have symmetric or asymmetric effects on the real exchange rate? Empirical evidence from Indonesia. The World Economy, forthcoming.

Bannigidadmath, D., Narayan, P., 2015. Stock return predictability and determinants of predictability and profits. Emerg. Mark. Rev. 26, 153–173.

Benassy-Quere, A., Mignon, V. & Penot, A., 2007. China and the relationship between the oil price and the Dollar. Energy Policy, 35, 5795-5805.

Bénassy-Quéré, A., Mignon, V., Penot, A., 2007. China and the relationship between the oil price and the dollar. Energy Policy 35, 5795-5805.

Benhmad, F., 2012. Modelling nonlinear Granger causality between oil prices and US dollar: a wavelet approach. Economic Modelling 29, 1505-1514.

Buetzer, S., Habib, M.M., Stracca, L., 2016. Global exchange rate configurations: Do oil shocks matter? IMF Economic Review 64, 443-470.

Campbell, J.Y, Thompson, S.B., 2008. Predicting excess stock returns out of sample: can anything beat the historical average? Review of Financial Studies 21, 1509–1531.

Chaudhuri, K., Daniel, B.C., 1998. Long-run equilibrium real exchange rates and oil prices. Economics Letters, 58, 231-238.

Chen, S.S., Chen, H.C., 2007. Oil price and real exchange rates. Energy Economics 29, 390-404.

Chen, Y., Rogoff, K., Rossi, B., 2010. Can exchange rates forecast commodity prices? Quarterly Journal of Economics 125, 1145-1194.

Clark, T.E., West T.D., 2007. Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics, 138, 291–31.

Cunado, J., Perez de Gracia, F., 2003. Do oil price shocks matter? Evidence for some European countries. Energy Economics 25, 137-154.

Cunado, J., Perez de Gracia, F., 2005. Oil prices, economic activity and inflation: evidence for some Asian countries. Quarterly Review of Economics and Finance 45, 65-83.

Devpura, N., Narayan, P.K., Sharma, S.S., 2018. Is stock return predictability time varying? Journal of International Financial Markets, Institutions and Money 52, 152–172.

Ferraro, D., Rogoff, K., Rossi, B., 2015. Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates. Journal of International Money and Finance 54, 116-141.

Golub, S., 1983. Oil prices and exchange rates. The Economic Journal 93, 579-593.

Hamilton, J.D., 1983. Oil and the macroeconomy since World War II. Journal of Political Economy 91, 228-248.

Hamilton, J.D., 1988. A neoclassical model of unemployment and the business cycle. Journal of Political Economy 96, 593-617.

Hamilton, J.D., 2003. What is an oil shock? Journal of Econometrics 113, 363-398.

Hamilton, J.D., 2009. Oil and the macroeconomy. In S.N. Durlauf, and L.E. Blume (eds). The New Palgrave Dictionary of Economics, Palgrave Macmillan.

Hamilton, J.D., 2011. Historial Oil Shocks. NBER Working Paper 16790.

Hooker, M.A., 1996. What happened to the oil price-macroeconomy relationship? Journal of Monetary Economics 38, 195-213.

Huang, Y., Guo, F., 2007. The role of oil price shocks on China's real exchange rate. China Economic Review 18, 403-416.

Huang, B.N., Lee, C.C., Chang, Y.F., Lee, C.C., 2020. Dynamic linkage between oil prices and exchange rates: new global evidence. Empirical Economics, forthcoming.

IEA- International Energy Agency, 2019. World Energy Outlook. Paris.

IMF- International Monetary Fund, 2019. World Economic Outlook Database. Washington, D.C.

Ji, Q., Liu, B.Y. and Fan, Y. 2019. Risk dependence of CoVaR and structural change between oil prices and exchange rates: A time-varying copula model. Energy Economics 77, 80-92.

Jones, C., Kaul, G., 1996. Oil and the stock markets. Journal of Finance 51, 463-491.

Kilian, L., 2008. The economic effects of energy price shocks. Journal of Economic Literature 46, 871-909.

Krugman, P., 1983. Oil shocks and exchange rate dynamics, in J.A. Frenkel (ed.), Exchange Rates and International Macroeconomics. University of Chicago Press, Chicago, 259-284.

Kumar, S., 2019. Asymmetric impact of oil prices on exchange rate and stock prices. The Quarterly Review of Economics and Finance 72, 41-51.

Lewellen, J., 2004. Predicting returns with financial ratios. Journal of Finance and Economics, 74, 209–235.

Lizardo, R.A., Mollick, A.V., 2010. Oil price fluctuations and U.S. dollar exchange rates. Energy Economics, 32, 399-408.

Moosa, I., 2013. Why is it so difficult to outperform the random walk in exchange rate forecasting? Applied Economics 45 (23), 3340–3346.

Moosa, I.A., Burns, K., 2012. Can exchange rate models outperform the random walk? Magnitude, direction and profitability as criteria. International Economics 65, 473–490.

Moosa, I., Burns, K., 2014a. The unbeatable random walk in exchange rate forecasting: reality or myth? Journal of Macroeconomics 40, 69–81.

Moosa, I., Burns, K., 2014b. Error correction modelling and dynamic specifications as a conduit to outperforming the random walk in exchange rate forecasting. Applied Economics 46 (25), 3107–3118.

Moosa, I., Burns, K., 2014c. A reappraisal of the Meese–Rogoff puzzle. Applied Economics 46 (1), 30-40.

Mork, K.A., 1989. Oil and the macroeconomy when prices go up and down: an extension of Hamilton's results. Journal of Political Economy 97, 740-744.

Narayan, S., 2013. Foreign exchange markets and oil prices in Asia. Journal of Asian Economics 28, 41-50.

Narayan, P.K., Gupta, R., 2015. Has oil price predicted stock returns for over a century? Energy Economics 48, 18–23.

Narayan, P.K., Bannigidadmath, D., 2015. Are Indian stock returns predictable? Journal of Banking and Finance 58, 506–531.

Narayan, P.K., Phan, D.H.B., Sharma, S.S., Westerlund, J., 2016. Are Islamic stock returns predictable? A global perspective. Pacific Basin Finance Journal 40 (A), 210–223.

Phan, D.H.B., Sharma, S.S., Narayan, P.K., 2015. Stock return forecasting: some new evidence. Int. Rev. Financ. Anal. 40, 38–51.

Reboredo, J.C., 2012. Modelling oil price and exchange rate co-movements. Journal of Policy Modeling 34, 419-440.

Salisu, A.A., Adekunle, W., Alimi, W.A. & Emmanuel, Z., 2019b. Predicting exchange rate with commodity prices: New evidence from Westerlund and Narayan (2015) estimator with structural breaks and asymmetries. Resources Policy 62 (2019) 33–56.

Salisu, A. A. & Mobolaji, H. (2013). Modeling returns and volatility transmission between oil price and US–Nigeria exchange rate. Energy Economics, 39(C), 169-176.

Salisu, A.A. & Isah, K., 2017. Revisiting the oil price and stock market nexus: A nonlinear Panel ARDL approach. Economic Modelling, 66(C), 258-271.

Salisu, A.A., Swaray, R., Oloko, T.F., 2019a. Improving the predictability of the oil-US stock nexus: the role of macroeconomic variables. Econ. Modell. 76 (C), 153–171.

Salisu, A.A. & Oloko, T. F. (2015). Modeling oil price–US stock nexus: A VARMA–BEKK–AGARCH approach. Energy Economics, 50(C), 1-12.

Shin, Y., Yu, B., Greenwood-Nimmo, M., 2014. Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework, in Anonymous Festschrift in Honor of Peter Schmidt. Springer, 281-314.

Turhan, M.I., Sensoy, A., Hacihasanoglu, E., 2014. A comparative analysis of the dynamic relationship between oil prices and exchange rates. Journal of International Financial Markets Institutions and Money 32, 397-414.

Westerlund, J., Narayan, P.K., 2012. Does the choice of estimator matter when forecasting returns? Journal of Banking and Finance, 36, 2632–2640.

Westerlund, J., Narayan, P.K., 2015. Testing for predictability in conditionally heteroskedastic stock returns. Journal of Finance and Economics, 13(2), 342–375.

Wu, C.C., Chung, H., Chung, H., 2012. The economic value of co-movement between oil price and exchange rate using copula-based GARCH models. Energy Economics 30, 270-282.