

Stock Markets and Exchange Rate Behaviour of the BRICS

Afees A. Salisu^{*}, Juncal Cuñado^{**}, Kazeem Isah^{***} and Rangan Gupta^{****}

Abstract

Relying on the Uncovered Equity Parity, we examine whether stock returns contain useful information that can be exploited to improve the forecast accuracy of exchange rate movements of the BRICS using a long range of data sample. Thus, we formulate a predictive model that links exchange rate movements to stock return differential between the domestic market and the foreign (US) market. We also test for any probable asymmetric relationship between the two variables while also accounting for the role of observed common (global) factor such as oil price. We find a positive relationship between stock return differential and exchange rate return for three of the BRICS countries namely Brazil, India and South Africa, thus validating the UEP hypothesis while a contrasting evidence is observed for China as well as Russia (after accounting for “asymmetry” effect”). Our in-sample and out-of-sample forecasts validate the significance of the predictive content of stock returns for exchange rate movements of the BRICS while accounting for the role of observed common (global) factor and asymmetry may further improve the forecast accuracy. Our results have implications for portfolio diversification and foreign exchange management.

Keywords: Stock market, Exchange rate, Uncovered Equity Parity, Forecast evaluation
JEL Codes: F31; G11; G15

^{*} Centre for Econometric & Allied Research, University of Ibadan, Ibadan, Nigeria. Email: adebare1@yahoo.com.

^{**} Economics Department, University of Navarra, Spain. Email: jcunado@unav.es

^{***} Centre for Econometric & Allied Research, University of Ibadan, Ibadan, Nigeria. Email: kzamboja@yahoo.com.

^{****} Economics Department, University of Pretoria, South Africa. Email: Rangan.Gupta@up.ac.za

1. Introduction

The BRICS (Brazil, Russia, India, and China, South Africa) countries¹ have played an increasingly important role in the world economy in the last two decades, and investors, looking for return differentials and diversification opportunities, have shifted their interest to these countries. In fact, the BRICS nations not only represent 42% of the total global population and 23% of total global GDP (IMF, 2019), but they also attracted 20% of the world Foreign Direct Investment (FDI) inflows and received 17% of the FDI outflows in 2018 (UNCTAD, 2019). Moreover, the excess returns of emerging markets have been higher than in developed markets during the last decades, and emerging market stock returns have also had a low correlation with developed market returns, providing international investors with favorable risk and return tradeoffs and risk diversification opportunities. Furthermore, and according to the predictions in a 2010 report from Goldman Sachs, China could surpass the US in equity market capitalization terms by 2030 and become the single largest equity market in the world (Moe et al., 2010), while by that year, the four BRICs would account for 41% of the world's market capitalization. Unlike exchange rates in developed economies, BRICS countries' exchange rates, have not been allowed to float freely, but they have been strictly controlled by different currency policies (Jiang, 2019) until recently, so that exchange rates in these countries could respond differently to the investment flows. 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. Moreover, 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. Analyzing to what extent and in which direction stock return differentials may drive exchange rate movements will be of interest for foreign investors, and for the design of exchange rate policies in those countries where governments can intervene to manage the value of the exchange rate. That is, it would be interesting to test whether strong stock markets will lead to strong or weak currencies for these emerging economies.

Since the seminal paper by Meese and Rogoff (1983a, 1983b) showing that exchange rate forecasting models were unlikely to outperform the random walk prediction, many attempts have

¹ In 2001, the term BRIC was coined for Brazil, Russia, India, and China. South Africa joined this group of countries in 2010, leading to BRICS.

been made to predict exchange rate movements (Berkowitz and Giorgianni, 2001; Kilian and Taylor, 2003; Abhyankar et al., 2005; Bacchetta et al., 2010; Rossi, 2013). As an example, according to the Uncovered Equity Parity (UEP), when foreign equity holdings outperform domestic holdings, domestic investors are exposed to higher exchange rate risk and hence, rebalance their portfolio repatriating some of the foreign equity to decrease their exchange rate risk. By doing so, foreign currency is sold, leading to foreign currency depreciation (Curcuro et al., 2014; Capiello and De Santis, 2005, 2007; Hau and Rey, 2006; Chen and Hsu, 2019), suggesting that a strong (weak) stock market precedes a weak (strong) currency.

Although the empirical literature supports, in general², the UEP hypothesis in advanced and developed economies (Curcuro et al., 2014; Hau and Rey, 2006; Capiello and De Santis, 2007; Kim, 2011; Melvin and Prins, 2015; Gelman et al., 2015; Chen and Hsu, 2019), the results are scarce and not conclusive for developing countries (Kim, 2011; Baur and Miyakawa, 2013; Aftab et al., 2018). For example, for developed countries, Hau and Rey (2006) find strong support when testing the hypothesis for 17 OECD countries vis-à-vis the United States, show that the correlations are stronger in those countries with higher equity market capitalization relative to GDP, and conclude that the exchange rate dynamics are related to equity market development. Curcuro et al. (2014) also find support for the UEP hypothesis when they analyze the US economy. Kim (2011) suggests that the reaction by monetary authorities to exchange rate movements through policy rates could cause the failure of the UEP hypothesis in emerging markets. Baur and Miyakawa (2013) find empirical support for the UEP for only a relatively small number of currencies, such as the US dollar, the UK pound, the Swiss franc or the Japanese yen, when they analyze the behavior of 53 currencies. Aftab et al. (2018) analyze the relationship between the two variables for six East Asian emerging markets (Indonesia, Korea, Malaysia, The Philippines, Thailand and Singapore) using monthly data from August 2005 to December 2014 finding a negative relationship between the two variables, that is, they find that a positive stock return differential is followed by a currency appreciation, the opposite to the prediction under the UEP hypothesis.

In this context, the objective of this paper is to analyse the ability of stock returns differentials to predict exchange rate movements of the BRICS countries, and thus, to test whether the UEP

² Evidence of a negative correlation between stock return differentials and Exchange rates are also found in the literature (see, for example, Cenedese et al., 2016).

hypothesis holds for these countries. This paper contributes to the literature on exchange rates predictability in several ways. First, unlike most of the literature, we examine the exchange rate predictability using stock return differentials in a sample of emerging countries. Since each of the BRICS countries has chosen different exchange rate regimes or currency interventions, the response of exchange rates to stock return differentials could be different in each of the countries. Second, while most of the literature focuses on in-sample predictability of exchange rates, this paper considers both in-sample and out-of-sample forecast evaluation. Because in-sample predictability may not necessarily translate into improved out-of-sample forecast (Chen and Hsu, 2019), extending forecast analyses to capture the latter is crucial particularly for policy decisions. Up to our knowledge, Chen and Hsu (2019) is the only paper that analyses out-of-sample forecast ability of stock return differentials for exchange rate movements, although their analysis includes the seven most-traded currencies (the US dollar, euro, Japanese yen, British pound, Australian dollar, Swiss franc and Canadian dollar), while our paper focuses on the currencies of the BRICS nations. Third, this paper contemplates the possibility of asymmetric responses of exchange rates to oil prices, allowing that exchange rates might react differently to positive and negative stock return differentials (Aftab et al., 2019). Fourth, and based on the relevance of BRICS countries in the generation and consumption of energy³, we also control for a common global factor, oil prices, when testing the predictive power of stock return differential for exchange rate movements. Finally, and for robustness purposes, we analyse the predictive power of stock returns differential to predict exchange rate movements of the UK economy.

The main results show a positive relationship between stock return differential and exchange rate return, and thus, they support the UEP hypothesis, for Brazil, India and South Africa, while a contrasting result for China and Russia. Moreover, for all the BRICS countries, in-sample and out-of-sample forecasts suggest that stock return differentials are a good predictor of exchange rate returns, while accounting for the role of observed common factor (oil prices) and asymmetry improves the exchange rate predictability. Finally, the main results of the paper for the BRICS countries are consistent with those obtained for a developed economy such as the UK.

³ Note that 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 and China and India stand as the world's first and third net crude oil importers (IEA, 2019).

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 discusses the empirical results, and finally, Section 5 contains some concluding remarks.

2. Data and Preliminary Analyses

To achieve the study objective, we utilize historical monthly data for both exchange rate and stock returns of the BRICS countries. The predicted series (i.e. exchange rate measured as the cost of domestic currency to 1 US dollar) is expressed in log return form for the purpose of empirical analysis while the predictor series (i.e. stock return differential) is computed as the difference between stock log returns of the domestic stock market and that of the foreign stock market.⁴ However, while both exchange rate and stock data are obtained from Global Financial Data,⁵ the start date varies across countries due to data availability. For instance, the start date for Brazil is January 1954, while it is December 1994 and July 1920 for Russia and India, respectively. For China and South Africa, the start date is December 1992 for the former and January 1910 for the latter. Nonetheless, all the countries have a uniform end date which is June 2020.

As customary for empirical analysis, we render some descriptive statistics for the relevant series. In Table 1, we present the mean and standard deviation statistics for exchange rate return and stock return differential. Essentially, we find that Brazil has the highest level of depreciation over the period under consideration followed by the Russian ruble, while the Chinese Yuan appears to be the strongest and equally doubles as the currency with the least standard deviation value. In other words, Yuan enjoys a relatively stable exchange rate, on the average, over the period under study. On the predictor series, we find that the mean values for stock return differential are positive for Brazil, Russia and South Africa while they are negative for India and China. These statistics seem to suggest that the larger the values of the stock return differential, the larger the depreciation of the domestic currency relative to the reference currency. In panel B, we offer some unit root tests, a requirement for time series analysis. We consider both the

⁴ In any case, expressing the series in return form helps to circumvent the problem of unit root typical of most financial series expressed in price index form. Note, we also follow Chen and Hsu (2019) in this regard.

⁵ <http://www.globalfinancialdata.com/>. The names of the respective stock indices used are: Brazil: Brazil Bolsa de Valores de Sao Paulo (BOVESPA) Stock Index; Russia: MOEX Russia Composite Index; India: Bombay Stock Exchange (BSE) Index; China: Shanghai Stock Exchange (SSE) Composite Index; South Africa: FTSE/Johannesburg Stock Exchange (JSE) All-Share Index, and; US: S&P 500 Index.

Augmented Dickey Fuller (ADF) test and the GARCH-based unit root test of Narayan & Liu (2015) for robustness. The results consistently reject the null hypothesis of unit root for the relevant series regardless of the choice of unit root test. In the next section, we formulate a predictive model that accommodates the outcome of the unit root test results.

Table 1: Preliminary results

	Exchange rate return		Stock return diff.		Obs.
Panel A: Descriptive statistics					
	<i>Mean</i>	<i>Std. Dev.</i>	<i>Mean</i>	<i>Std. Dev.</i>	
Brazil	4.21	8.66	4.84	20.18	797
Russia	0.98	5.70	1.05	9.92	306
India	0.28	2.50	-0.05	5.90	1199
China	0.06	2.31	-0.63	8.33	330
S-Africa	0.28	2.89	0.18	5.17	1325
Panel B: Unit root test					
	Exchange rate return		Stock return diff.		
	ADF	NL (2015)	ADF	NL (2015)	
Brazil	-6.95***	-0.35***	19.09**	-0.61***	
Russia	-12.68***	-0.51***	-14.22***	-0.81***	
India	-32.31***	-1.01***	-27.10***	-0.79***	
China	-17.47***	-1.00**	-15.33***	-0.85***	
S-Africa	-29.14***	-0.75***	-29.64***	-0.80***	

Note: Std. Dev. in “Panel A” denotes standard deviation; “Obs.” is for observations and “diff.” as used in Stock return diff. denotes differential; ADF denotes Augmented Dickey-Fuller; NL (2015) is for Narayan and Liu (2015) GARCH-based unit root test; ***, **, & * indicate the rejection of the null hypothesis of unit root at 1%, 5% and 10%, respectively.

3. Methodology

The theoretical link between stock return differential and exchange rate is rooted in the uncovered equity parity (UEP). According to the UEP, when foreign equity holdings outperform their domestic counterparts, domestic investors are exposed to higher exchange rate and hence repatriate some of the foreign equity to decrease their exchange rate risk (Curcuro et al., 2014). This rebalancing usually results in the selling of foreign currency thus leading to foreign currency depreciation. Since the UEP theory suggests that a strong equity market is associated with a weak currency because of portfolio rebalancing (Chen & Hsu, 2019), a positive association is hypothesized between stock return differential and exchange rate. Some empirical studies have offered evidence in support of the UEP (i.e. positive correlation between the two variables in question) (see Cappiello & De Santis, 2005, 2007; Hau & Rey, 2006; Kim, 2011; Curcuro et al.,

2014; Gelman et al., 2015; Chen & Hsu, 2019) while there is also evidence of a negative correlation (see Bohn & Tesar, 1996 ; Griffin et al., 2004; Malliaropulos, 2008; Wong & Li, 2013; Chabot et al., 2014; Ülkü et al., 2016; Cenedese et al., 2016; Chen & Hsu, 2019). In other words, the relationship can run either way.⁶ We construct a predictive model that links exchange rate to stock return differential in line with the UEP:⁷

$$e_t = \alpha + \beta (r_t^d - r_t^f) + \varepsilon_t \quad [1]$$

where e_t is the exchange rate return computed as log difference of nominal exchange rate (s_t) in month t , and US dollar (USD) is the reference (foreign) currency. Hence, an increase in s_t implies a depreciation of the domestic currency relative to USD while a decrease in s_t implies otherwise. The predictor ($r_t^d - r_t^f$) is the stock return differential which measures the difference in the stock returns of domestic and foreign stock markets where the latter is the US stock market being the reference currency for e_t . Note that r_t^d is the domestic stock return series while r_t^f represent the foreign stock returns and both are computed as first difference of log of stock price index. We test the null hypothesis of no predictability $\beta = 0$ against the alternative hypothesis of predictability $\beta \neq 0$. As noted in the previous section on preliminary analysis and given the way the variables are captured in the model, we do not suspect any unit root problem, thus, the t test statistic obtained from the ordinary least squares estimator is assumed relatively unbiased and efficient and should suffice for the predictability analysis.⁸

One of the limitations of equation [1] is that it assumes that positive and negative values of ($r_t^d - r_t^f$) will have identical effect on exchange rate movements. However, exchange rates are found to respond asymmetrically to macro fundamentals (although not from the perspective of stock return differential) (see Ferraro et al., 2015; Salisu et al., 2019). Consequently, we construct a model where the response of exchange rate to positive and negative stock differential is distinctly evaluated:

⁶ See Chen and Hsu (2019) for a review of related studies on the subject.

⁷ Note that the UEP condition suggests a contemporaneous relationship between exchange rate movements and stock return differentials. Thus, while the interest is to examine the predictive power of stock return differentials for exchange rate movements, we are also able to test the UEP condition for the countries under examination.

⁸ The outcome of additional preliminary tests such as persistence, endogeneity bias and conditional heteroscedasticity tests as discussed in Westerlund and Narayan (2012, 2015) whose results are available on request also favours the chosen estimator.

$$e_t = \alpha + \beta(r_t^d - r_t^f) + \gamma D_t + \lambda D_t * (r_t^d - r_t^f) + \varepsilon_t \quad [2]$$

where $D = 1$ if $(r_t^d - r_t^f) > 0$ and zero otherwise. As a consequence, β measures negative asymmetry (i.e. effect of negative stock differential on exchange rate) while positive asymmetry is measured as $\beta + \lambda$ with the joint significance determined using the Wald test. The presence of asymmetry or otherwise is evaluated with λ which can also be referred to as differential slope coefficient used to determine if the difference in the negative and positive asymmetry coefficients is statistically significant. For robustness, we also account for a global factor, oil price, in the predictive model for exchange rate (see Ferraro et al., 2015; Chen & Hsu, 2019; Salisu et al., 2019) and thus, we are able to evaluate the sensitivity of the relationship between stock differential and exchange rate to control variables.

Finally, we evaluate the out-of-sample forecast power of stock differential for exchange rate using the h-ahead forecast model specified as:

$$e_{t+h} = \alpha + \beta(r_t^d - r_t^f) + \varepsilon_{t+h} \quad [3]$$

where h denotes 1, 3, 6, 12 and 24 out-of-sample forecast horizons while other variables and parameters are as previously defined. On the forecast evaluation, we split and consider only 75% of the full data sample for the in-sample forecasts and subsequently obtain the out-of-sample forecasts over the considered forecasting horizons using the rolling window approach. The forecast evaluation of the predictor is rendered using two pair-wise forecast measures, namely Campbell-Thompson (CT, 2008) and Clark and West (CW, 2007) tests.⁹ These measures are particularly useful when dealing with nested predictive models. The (CT, 2008) test is specified as:

$$CT = 1 - (M\hat{S}E_u / M\hat{S}E_r) \quad [4]$$

where $M\hat{S}E_u$ is the mean squared error obtained from the unrestricted model, which accommodates stock differential as a predictor in the exchange rate model (say equation [1]) and $M\hat{S}E_r$ is the mean squared error obtained from the restricted model (such as, the historical average or constant return model) which ignores the role of stock differential. The terms $M\hat{S}E_r$ and $M\hat{S}E_u$ are respectively computed as $P^{-1} \sum (e_{t+h} - \hat{e}_{r,t+h})^2$ and $P^{-1} \sum (e_{t+h} - \hat{e}_{u,t+h})^2$

⁹ Given the nature of our time series dimension, the forecast evaluation is limited to the in-sample and a single out-of-sample forecast evaluation with one-week ahead period for brevity.

with P being the amount of predictions that the averages are computed. Based on the CT (2008) test, the unrestricted model outperforms the restricted model if $CT > 0$ and vice versa if $CT < 0$. The CW (2007) test can be used to establish the statistical significance of the CT test. For a forecast horizon h , the CW (2007) test is specified as:

$$\hat{f}_{t+h} = M\hat{S}E_r - (M\hat{S}E_u - adj) \quad [5]$$

where \hat{f}_{t+h} is the difference in the forecast errors of the restricted and unrestricted models. While we have previously defined $M\hat{S}E_r$ and $M\hat{S}E_u$, the term adj is included to adjust for noise in the unrestricted model and it is defined by $P^{-1} \sum (\hat{r}_{r,t+h} - \hat{r}_{u,t+h})^2$. The significance of \hat{f}_{t+h} is evaluated by regressing \hat{f}_{t+h} on a constant and the null hypothesis of a zero coefficient is rejected if this statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test) and +2.00 for 0.01 test (for a one sided 0.01 test) (see Clark and West, 2007).

4. Discussion of Results

4.1 In-sample predictability

Table 2 illustrates the predictability test of stock return differential for exchange rate movements of the BRICS. Confirming the Uncovered Equity Parity (UEP) hypothesis, we find a positive relationship between stock return differential and exchange rate return of three of the BRICS countries namely, Brazil, India and South Africa. This implies that an increase in stock return differential (where domestic stock market outperforms the foreign stock market), will cause the domestic currency to depreciate relative to the foreign currency. As the domestic stock market offers higher expected returns, a domestic investor suffers a loss when investing abroad, and therefore should be compensated by the expected capital gain that occurs when the foreign currency appreciates (Chen & Hsu, 2019). However, beyond the fact that the coefficient on Russian exchange rate is not statistically significant (although, correctly signed), the predictability results for the Chinese Yuan tend to contradict the UEP prediction, but the results yet find support in Griffin et al. (2004); Hau & Rey (2006); Malliaropulos, 2008; Wong & Li (2013); Chabot et al. (2014), Ülkü et al. (2016) and Chen & Hsu (2019). This contrasting evidence to the UEP hypothesis can be attributed to return-chasing behaviour of investors, whereby investors decide to increase their holdings in market that have recently outperformed other markets. Thus, the

domestic currency of China is likely to appreciate when the domestic stock market outperforms the US market.

When we control for the role of changes in oil price in the nexus, measured as log of the first difference of the monthly spot price of West Texas Intermediate (WTI) crude oil, we find little or no difference in the direction of the nexus. That is, except for the magnitude of the impact of the nexus, where the coefficients on exchange rate return appear to be relatively higher for India, China, South Africa and even Russia in the model with control, the significance as well as the direction of the relationship remain the same for both models (with and without control). On whether accounting for “asymmetry” effect matters in the nexus, we find the null hypothesis of no asymmetry consistently rejected for all the BRICS countries with the exception of South Africa. This indicates that exchange rate responds differently to positive and negative stock return differential of the same magnitude. More specifically, exchange rates of the BRICS tend to respond more to negative stock return differential [where the foreign (US) stock market outperforms the domestic stock market] than the positive stock return differential [where the domestic stock market outperforms the foreign stock market]. On the whole, we find support for the UEP hypothesis in a number of the BRICS countries. More importantly, we find that the results are robust (i.e. insensitive) to exogenous conditions such as changes in oil price while accounting for whether asymmetry matters in the nexus.

Table 2: Predictability results

	Brazil	Russia	India	China	South Africa
Without Control	0.1315*** (0.0145)	0.0038 (0.0329)	0.0340*** (0.0121)	-0.0297** (0.0152)	0.0309** (0.0135)
With Control	0.1311*** (0.0144)	0.0172 (0.0325)	0.0352*** (0.0121)	-0.0301** (0.0152)	0.0350** (0.0152)
With Asymmetry					
Positive Asymmetry	0.1783*** (0.0160)	0.0926 (0.0572)	0.0731*** (0.0243)	0.0016 (0.0295)	0.0384 (0.0297)
Negative Asymmetry	-0.3375*** (0.0613)	-0.1313** (0.0654)	0.0067 (0.0236)	-0.0749** (0.0316)	-0.0311 (0.0332)
Asymmetry test	0.5158*** (0.0634)	0.2240** (0.0869)	0.0664** (0.0339)	0.0765* (0.0433)	0.0696 (0.0446)

Note: “Without Control” implies the original model with the predictor of stock return differential only, while “With Control” is an extension of the original model to include relevant control variables (i.e. oil price). “With Asymmetry” implies the model with distinct coefficients for positive stock return differential and negative stock return differential, while Asymmetry test is the Wald test for coefficient restriction used to test whether exchange rate responds differently to positive and negative stock return differentials. Values in parentheses - () are the standard errors of the coefficients, ***, ** & * indicate statistical significance at 1%, 5% and 10% levels respectively.

4.2 Forecast performance results

We further examine the in-sample and out-of-sample forecasting prowess of stock return differential for exchange rate movements. As noted previously, we use both the single (RMSE) and pairwise [Campbell-Thompson (C-T) and Clark-West (C-W)] forecast measures for the forecast evaluation exercise. We present in Table 3, the in-sample and out-of-sample forecast performance results using the RMSE measure. We consider out-of-sample forecast horizons of 1, 3, 6; 12; and 24 months. Although, the dominant position in the literature is that future exchange rates are difficult to forecast (see Moosa, 2013; Moosa & Burns, 2012, 2014a, 2014b, & 2014c), we however find that lower values of the RMSE for Model 1, Model 2, and Model 3 compared to the HA model (Model 4) which is the benchmark model for financial variables measured in return form.¹⁰ We also find that RMSE values tend to reduce after controlling for oil price changes and accounting for asymmetry effect in stock return differential. This outcome remains the same for both the in-sample and out-of-sample forecasts.

Since we are dealing with nested models, we complement the RMSE-based forecasts with the pairwise measures¹¹ and the results are presented in Tables 4 and 5 for C-T and C-W tests, respectively. A positive value of the C-T test implies the outperformance of the unrestricted model over the restricted model while a negative value of the test implies otherwise. As shown in Table 4, the C-T statistics are positive for all the variants of the stock-based model over the countries under consideration. Thus, any predictive model of exchange rate movements that accounts for stock return differential is more likely to outperform the one that ignores it, such as the historical average. Like the RMSE statistics, the C-T statistics seem to increase with the consideration of the mentioned control variable (oil price movements) and asymmetry effect in the stock differential series. This outcome is in line with the evidence of Chen & Hsu (2019) albeit with a focus on most traded currencies and without considering asymmetry effect. An extension of the Chen & Hsu

¹⁰ This is because the historical average model for return series is technically the random walk for the corresponding price index. For example, if we express our random walk for a price index (p) as:

$$\log(p) = \text{constant} + \log(p(-1)) + \text{error} \quad [1]$$

This can be equivalently expressed in return form as:

$$\log(p) - \log(p(-1)) = \text{constant} + \text{error} \quad [2]$$

Equation [2] is the historical average model for the return series which is an equivalent specification for the corresponding price series. This explains why most studies involving return predictability consider historical average model rather than random walk (see for example, Narayan & Gupta, 2015; Salisu and Vo, 2020; among others).

¹¹ The Diebold and Mariano (1995) test is not considered here since it is more suitable for non-nested models.

(2019) study to capture the emerging markets of the BRICS offers is crucial for possible generalization of the predictability stock markets for exchange rate movements.

Lastly, we test for the significance of the difference in the forecast errors of each of the stock-based models and the benchmark model using the C-W test and we present the results in Table 5. Like the C-T statistics, the C-W coefficients in Table 5 are predominantly positive, thus, ascertaining the potential of the stock-based predictive model in enhancing the accuracy of exchange rate forecasts of the BRICS relative to the benchmark model. This significance of the C-W test is largely evident for Brazil, India as well as Russia (after accounting for asymmetry effect). The conclusion here is straight forward. The various forecast measures lend support to the inclusion of stock return differential when modelling and forecasting exchange rate movements of emerging markets particularly those drawn from the BRICS bloc. In other words, emerging stock markets have predictive content for forecasting exchange rate movements. Two policy implications can be drawn from this outcome. First, financial analysts seeking for models that will improve their forecasts of exchange rate movements possibly for the purpose of portfolio diversification particularly between domestic and foreign stock markets will find our results insightful. Second, policy makers who are constantly pressured on how to stabilize exchange rate movements particularly for countries with managed floating exchange system may find the study useful as it offers an alternative approach, among other existing options, of determining when foreign exchange (FX) intervention will be required. For instance, where exchange rate is expected to depreciate based on the forecast from the stock-based predictive model, relevant policy authority may forestall or mitigate such depreciation via policy actions targeted at reducing domestic supply of FX, among others.

Table 3: RMSE – based forecast performance results

Forecast Horizon	Model 1				
	Brazil	Russia	India	China	South Africa
In-sample	8.9518	5.9106	2.6931	2.5711	2.6240
h=1	8.9500	5.9041	2.6916	2.5660	2.6227
h=3	8.9384	5.8820	2.6942	2.5560	2.6209
h=6	8.9208	5.8500	2.6925	2.5429	2.6175
h=12	8.9081	5.9879	2.6936	2.5145	2.6128
h=24	8.8727	6.0640	2.6770	2.4643	2.6014
	Model 2				
In-sample	8.9467	5.9043	2.6926	2.5710	2.6240
h=1	8.9445	5.8984	2.6911	2.5659	2.6227
h=3	8.9326	5.8764	2.6938	2.5559	2.6209
h=6	8.9156	5.8443	2.6920	2.5427	2.6175
h=12	8.9024	5.9616	2.6928	2.5143	2.6128
h=24	8.8667	6.0246	2.6763	2.4645	2.6014
	Model 3				
In-sample	8.6490	5.8375	2.6885	2.5568	2.6226
h=1	8.6469	6.0191	2.6870	2.5517	2.6213
h=3	8.6353	5.8350	2.6898	2.5416	2.6195
h=6	8.6152	5.8115	2.6880	2.5289	2.6162
h=12	8.5974	5.7784	2.6889	2.5009	2.6115
h=24	8.5571	5.9396	2.6725	2.5417	2.6001
	Model 4				
In-sample	9.4046	5.9108	2.7178	2.5857	2.6262
h=1	9.4025	5.9044	2.7164	2.5806	2.6249
h=3	9.3912	5.8823	2.7185	2.5705	2.6232
h=6	9.3725	5.8503	2.7168	2.5573	2.6198
h=12	9.3593	5.9884	2.7180	2.5289	2.5161
h=24	9.3260	6.0638	2.7008	2.4775	2.6038

Note: Model 1 is the model without control; Model 2 is the model with control; Model 3 is the model with asymmetry; Model 4 is the Historical Average model. The Clark & West test measures the significance of the difference in the forecast errors of two competing models. The smaller the RMSE value the better the forecast performance of a model.

Table 4: Campbell –Thompson (C-T) test –based forecast performance results

Forecast Horizon	Model 4 vs Model 1				
	Brazil	Russia	India	China	South Africa
In-sample	0.0482	3.66E-05	0.0091	0.0056	0.0009
h=1	0.0481	3.96E-05	0.0092	0.0057	0.0009
h=3	0.0482	5.48E-05	0.0089	0.0056	0.0009
h=6	0.0481	5.92E-05	0.0089	0.0056	0.0009
h=12	0.0481	7.23E-05	0.0090	0.0057	0.0009
h=24	0.0486	-2.85E-05	0.0088	0.0053	0.0008
		Model 4 vs Model 2			
In-sample	0.0486	0.0011	0.0092	0.0056	0.0009
h=1	0.0487	0.0010	0.0093	0.0057	0.0009
h=3	0.0488	0.0010	0.0091	0.0057	0.0009
h=6	0.0487	0.0010	0.0091	0.0057	0.0009
h=12	0.0488	0.0044	0.0092	0.0058	0.0009
h=24	0.0492	0.0064	0.0091	0.0052	0.0008
		Model 4 vs Model 3			
In-sample	0.0803	0.0124	0.0107	0.0111	0.0014
h=1	0.0804	0.0117	0.0108	0.0112	0.0014
h=3	0.0805	0.0120	0.0106	0.0112	0.0014
h=6	0.0807	0.0123	0.0106	0.0111	0.0013
h=12	0.0814	0.0081	0.0107	0.0111	0.0014
h=24	0.0824	0.0073	0.0104	0.0104	0.0014

Note: Model 1 is the model without control; Model 2 is the model with control; Model 3 is the model with asymmetry; Model 4 is the Historical Average model. The C-T test results are based on the forecast performance comparison of each of the stock-based models (i.e. Models 1, 2 & 3) against HA. Hypothetically, a positive C-T value implies that a particular stock-based model outperforms HA and the reverse holds if the statistic is negative.

Table 5: Clark & West (C-W) test –based forecast performance results

Forecast Horizon	Model 4 vs Model 1				
	Brazil	Russia	India	China	South Africa
In-sample	16.6254*** [3.9613]	0.0051 [0.1176]	0.2683*** [3.1265]	0.1509 [0.0102]	0.0237 [1.0042]
h=1	16.6029*** [3.9625]	0.0053 [0.1225]	0.2681*** [3.1281]	0.1502 [1.0096]	0.0237 [1.0064]
h=3	16.5755*** [3.9699]	0.0063 [0.1476]	0.2653*** [3.1008]	0.1488 [1.0081]	0.0240 [1.0203]
h=6	16.5076*** [3.9724]	0.0065 [0.1547]	0.2658*** [3.1164]	0.1474 [1.0110]	0.0237 [1.0104]
h=12	16.4115*** [3.9881]	0.0076 [0.1839]	0.2663*** [3.1418]	0.1454 [1.0203]	0.0235 [1.0069]
h=24	16.2731*** [4.0316]	0.0002 [0.0065]	0.2628*** [3.1406]	0.1399 [1.0261]	0.0238 [1.0302]
		Model 4 vs Model 2			
In-sample	16.8071*** [4.0237]	0.1546 [0.5870]	0.2731*** [3.2541]	0.1519 [0.9983]	0.0237 [1.0015]
h=1	16.7927*** [4.0269]	0.1470 [0.5604]	0.2729*** [3.2253]	0.1513 [0.9980]	0.0237 [1.0037]
h=3	16.7707*** [4.0350]	0.1464 [0.5613]	0.2699*** [3.2256]	0.1499 [0.9966]	0.0240 [1.0176]
h=6	16.6951*** [4.0366]	0.1457 [0.5674]	0.2707*** [3.2446]	0.1486 [1.0000]	0.0237 [1.0178]
h=12	16.6067*** [4.0548]	0.4011 [1.3801]	0.2730*** [3.2911]	0.1467 [1.0103]	0.0235 [1.0036]
h=24	16.4763*** [4.1047]	0.5590** [1.9266]	0.2691*** [3.2869]	0.1396 [1.0053]	0.0238 [1.0286]
		Model 4 vs Model 3			
In-sample	27.2855*** [5.3901]	1.7231*** [3.0595]	0.3170*** [2.8064]	0.2971 [1.0240]	0.0384 [1.2279]
h=1	27.2593*** [5.3811]	1.6767*** [2.9800]	0.3168*** [2.8080]	0.2965 [1.0260]	0.0384 [1.2298]
h=3	27.2063*** [5.3634]	1.6879*** [3.0257]	0.3133*** [2.7824]	0.2950 [1.0290]	0.0386 [1.2396]
h=6	27.1420*** [5.3371]	1.6890*** [3.0666]	0.3137*** [2.7946]	0.2900 [1.0237]	0.0380 [1.2231]
h=12	27.1167*** [5.1304]	1.4231** [2.5793]	0.3152*** [2.8248]	0.2844 [1.0274]	0.0377 [1.2224]
h=24	26.9773 [5.2034]	1.3619** [2.5227]	0.3103*** [2.8178]	0.2720 [1.0278]	0.0382 [1.2499]

Note: Model 1 is the model without control; Model 2 is the model with control; Model 3 is the model with asymmetry; Model 4 is the Historical Average model. The Clark & West test measures the significance of the difference in the forecast errors of two competing models. The null hypothesis of a zero coefficient is rejected if this statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test) and +2.00 for 0.01 test (for a one sided 0.01 test) (see Clark and West, 2007). Values in square brackets – [] are for t-statistics, while ***, ** & * indicate statistical significance at 1%, 5% and 10% levels respectively.

4.3 Additional results

For robustness purpose, we consider a developed economy, the UK economy, in order to complement the analysis rendered for the emerging economies of the BRICS. The reference country, the US, remains unchanged. Therefore, the stock differential is computed as the difference between the (FTSE All Share Stock Index (ALSI)) stock returns of the UK (which is considered as the domestic stock market in this case derived from Global Financial Data) and that of the US (i.e. the foreign stock market). Hence, we further provide additional results using the case of economies of the same status, i.e. UK stock return differential relative to US. Another important attraction to the UK among other developed economies (aside US which is the reference country here) is the availability of a long range of data of over two centuries dating back to 1791. The results that utilize the entire dataset, albeit with the control variable (oil price changes) due to data limitation are presented in the appendix (see Table A1). Notwithstanding, we consider a reduced size starting from 1859 (over a century) being the earliest period for West Texas Intermediate (WTI) crude oil price (obtained from Global Financial Data as well) in order to accommodate the stock-based predictive model with control variable. We focus on the forecast evaluation of the alternative models previously analyzed for the BRICS and the results are presented in Table 7. The forecast performance results from both the single method using RMSE and the pairwise methods (i.e. C-T & C-W) consistently support our earlier findings. All the variants of the stock-based model outperform the benchmark model both for the in-sample and out-of-sample forecasts. A look at Table A1 in the appendix section of the paper further suggests that the conclusion remains the same irrespective of the data sample. Given the consideration of both emerging and developed economies in this study, our evidence offers some level of generalization about the predictive prowess of stock markets for forecasting exchange rate movements.

Table 6: Forecast performance results

		Single measure method: RMSE					
Forecast Horizon		Model 1	Model 2	Model 3	Model 4		
In-sample		2.0985	2.0871	2.0963	2.1275		
	h=1	2.1000	2.0885	2.0978	2.1291		
	h=3	2.1005	2.0891	2.0984	2.1297		
	h=6	2.1070	2.0956	2.1048	2.1360		
	h=12	2.1288	2.1173	2.1262	2.1574		
	h=24	2.1274	2.1166	2.1248	2.1554		
		Pairwise method					
Forecast Horizon		C-T test			C-W test		
		Model 4 vs Model 1	Model 4 vs Model 2	Model 4 vs Model 3	Model 4 vs Model 1	Model 4 vs Model 2	Model 4 vs Model 3
In-sample		0.0136	0.0190	0.0146	0.2449*** [3.4283]	0.3408*** [4.0834]	0.2635*** [3.3844]
	h=1	0.0136	0.0190	0.0146	0.2455*** [3.4388]	0.3413*** [4.0918]	0.2637*** [3.3900]
	h=3	0.0136	0.0190	0.0146	0.2455*** [3.4434]	0.3412*** [4.0961]	0.2636*** [3.3930]
	h=6	0.0135	0.0189	0.0146	0.2453*** [3.4431]	0.3414*** [4.1017]	0.2640 [3.4008]
	h=12	0.0132	0.0186	0.0145	0.2452*** [3.4532]	0.3417*** [4.1208]	0.2657*** [3.4348]
	h=24	0.0129	0.0179	0.0141	0.2418*** [3.4295]	0.3363*** [4.0827]	0.2618*** [3.4084]

Note: Model 1 is the model without control; Model 2 is the model with control; Model 3 is the model with asymmetry; Model 4 is the Historical Average model. The C-T test results are based on the forecast performance comparison of each of the stock-based models (i.e. Models 1, 2 & 3) against HA. Hypothetically, a positive C-T value implies that a particular stock-based model outperforms HA and the reverse holds if the statistic is negative. The Clark & West test measures the significance of the difference in the forecast errors of two competing models. The null hypothesis of a zero coefficient is rejected if this statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test) and +2.00 for 0.01 test (for a one sided 0.01 test) (see Clark and West, 2007). Values in square brackets – [] are for t-statistics, while ***, ** & * indicate statistical significance at 1%, 5% and 10% levels respectively.

5. Conclusion

This study seeks to examine the predictive power of stock return differential for exchange rate movements of the BRICS. We rely on the Uncovered Equity Parity (UEP) hypothesis in the formulation of a bivariate predictive model that links exchange rate to stock return differential. While several empirical studies have examined the validity or otherwise of the UEP hypothesis (see for example, Cappiello and De Santis, 2005, 2007; Hau and Rey, 2006; Kim, 2011; Curcuru et al., 2014; Gelman et al., 2015; Chen & Hsu, 2019), their analyses are limited to in-sample

predictability which does not offer sufficient information about the out-of-sample forecast ability of stock markets for exchange rate movements. This is the motivation for the study and the only exception is Chen & Hsu (2019) albeit with a focus on the developed economies. In addition to considering emerging economies of the BRICS, we also account for asymmetry effect which assumes that exchange rate may respond differently to positive and negative stock return differentials. We also control for a common global factor (oil price) in the estimation process and thus, we arrive at three variants of the stock-based model for exchange rate while historical average is the benchmark model. The forecast evaluation involves comparing the variants of the stock-based model with the benchmark model using both the single (RMSE) and pairwise (C-T & C-W) forecast measures and multiple out-of-sample forecast horizons [1,3,6,12, and 24 months] are analyzed. Our results support a positive relationship between stock return differential and exchange rate return for three of the BRICS countries namely Brazil, India and South Africa, thus validating the UEP hypothesis while a contrasting evidence is observed for China as well as Russia (after accounting for “asymmetry” effect”). The significance of the predictive content of stock markets for exchange rate movements is evident for both the in-sample and out-of-sample forecasts while accounting for oil price movements and asymmetry may further improve the forecast accuracy. We note that financial/investment analysts may find the results useful for the purpose of portfolio diversification between domestic and foreign portfolios likewise policy makers in terms of stabilizing exchange rates.

An extension of this study that utilizes sectoral stock data and by implication panel data forecasting techniques and or forecast combination/averaging methods would further enrich the literature on the subject. This may however require using trade-weighted exchange rates with the relative sectoral trading volume for domestic and foreign stock markets used as the weighting scheme to accommodate some level of heterogeneity in both exchange rate and stock return differential. This is an area we set aside for future research.

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Appendix

Table A1: Forecast performance results for UK with August 1791 the start date

Single measure method: RMSE						
Forecast Horizon	Model	Model 2	Model 3	Model 4		
In-sample	2.6839		2.6847	2.6792		
h=1	2.6833		2.6840	2.6785		
h=3	2.6820	Not Applicable	2.6827	2.6772		
h=6	2.6800		2.6807	2.6753		
h=12	2.6762		2.6769	2.6715		
h=24	2.6685		2.6692	2.6638		
Pairwise method						
Forecast Horizon	C-T test			C-W test		
	Model 4 vs Model 1	Model 4 vs Model 2	Model 4 vs Model 3	Model 4 vs Model 1	Model 4 vs Model 2	Model 4 vs Model 3
In-sample	0.0002		0.0020	0.0075		0.0585
h=1	0.0003		0.0020	0.0075		0.0585
h=3	0.0003		0.0020	0.0075		0.0585
h=6	0.0003	Not Applicable	0.0020	0.0075	Not Applicable	0.0583
h=12	0.0003		0.0020	0.0075		0.0582
h=24	0.0003		0.0020	0.0075		0.0578
				[0.3006]		[1.3515]
				[0.3007]		[1.3516]
				[0.3008]		[1.3517]
				[0.3007]		[1.3515]
				[0.3007]		[1.3514]
				[0.3020]		[1.3512]

Note: Model 1 is the model without control; Model 2 is the model with control; Model 3 is the model with asymmetry; Model 4 is the Historical Average model. The C-T test results are based on the forecast performance comparison of each of the stock-based models (i.e. Models 1, 2 & 3) against HA. Hypothetically, a positive C-T value implies that a particular stock-based model outperforms HA and the reverse holds if the statistic is negative. The Clark & West test measures the significance of the difference in the forecast errors of two competing models. The null hypothesis of a zero coefficient is rejected if this statistic is greater than +1.282 (for a one sided 0.10 test), +1.645 (for a one sided 0.05 test) and +2.00 for 0.01 test (for a one sided 0.01 test) (see Clark and West, 2007). Values in square brackets – [] are for t-statistics, while ***, ** & * indicate statistical significance at 1%, 5% and 10% levels respectively.