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Predicting stock returns using crude oil prices: A firm level analysis of Nigeria's oil and gas sector

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ABSTRACT

The decision over asset holding is traditionally premised on the double-edge objective of returns maximization and risk minimization. While the class of assets held by a typical investor depends on his attitude towards risks, an optimal investment portfolio requires a strategic combination of alternative assets (commodities, T-bills, stocks etc). To this end, our paper analyzes the role of crude oil prices in predicting stock returns, in addition to the traditional factors, particularly the returns on risk-free assets (such as, T-bills) as enunciated by the Capital Asset Pricing Model (CAPM). We also consider the possibility of nonlinearities in the nexus between crude oil prices and stock returns of nine major oil and gas companies that are currently listed on the Nigerian Stock Exchange over the period of January 2014 to November 2019. Our results show significant in-sample predictability of stock returns using crude oil prices, thereby affirming our argument that oil price matters in the predictability of stock returns for some listed oil and gas firms in Nigeria. We also offer evidence for the role of asymmetries in the predictability of stock returns for the majority of the listed oil and gas companies in Nigeria. By implication, the increasing exposure of the earnings, vis-à-vis, the share prices of some major oil and gas companies to negative changes in global oil prices suggests the need for diversification of their scope of operations.

1. Introduction

The Nigerian economy is largely oil dependent, making it highly sensitive to movements in global crude oil prices. Oil price volatility matters for the investment decisions of prospective investors in Nigeria's oil and gas sector, most especially. This in turn affects the profitability of firms and hence the values of their shares on the domestic stock market (see, for instance, Gupta, 2016 and Soyemi et al., 2017). In the words of Kayalar et al. (2016), changes in crude oil prices are believed to affect stock markets through the channel of expectations. Meanwhile, Basher and Sadorsky (2006) argued that the impact of falling oil prices on stock market differs from country to country depending on whether the country is an oil exporter or an oil importer. In an oil exporting country, an increase in oil prices improves the trade balance, leading to a higher current account surplus and an improving net foreign asset position. At the same time, a rise in oil prices tends to increase private disposable income in oil exporting countries. This in turn enhances corporate profitability, boosts domestic demand and push up stock prices, thereby causing exchange rate to appreciate. In oil importing countries, the process works broadly in reverse: trade deficits are offset by weaker growth and, overtime, real exchange rate depreciates and stock prices decline (Basher and Sadorsky, 2006).

The extent to which stock prices are influenced by world oil price changes is explained by the theory of equity valuation, which defines the stock price as the sum of discounted values of expected future cash flows at different investment horizons (Jouini, 2013). Consequently, oil prices affect stock prices directly by impacting future cash flows or indirectly through an impact on the interest rate used to discount the future cash flows. In the absence of complete substitution effects between the factors of production, rising oil prices, for example, increases the cost of doing business, and for non-oil related companies, it reduces profits. Rising oil prices can also be passed on to consumers in form of higher prices, but this will reduce the demand for final goods and services and depress profits. In addition, rising oil prices are often seen as inflationary by

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policy makers, and central banks respond to inflationary pressures by reviewing interest rates upwards, which in turn affects the discount rate used in the stock pricing formula (Basher et al., 2012). Faced with initial oil price increases, the investors and the analysts would predict further oil price increases and estimate lower expected future cash flows, resulting in a lower stock value. But the fact that these expected future cash flows respond differently to positive and negative oil price changes implies that the effect of an oil price shock on stock prices should also depend on the nature of asymmetry of the shock both in terms of the size and sign of the shock (Salisu et al., 2019b).

Moreover, a number of studies have been conducted on the impact of oil prices/market indices on stock market indices for developed and emerging markets, albeit at an aggregative level (see, for instance, Jones and Kaul, 1996; Kilian and Park, 2009; Aloui et al., 2012; Basher et al., 2012; Chang and Yu, 2013; Jouini, 2013; Cuando and Perez de Gracia, 2014; Hamma et al., 2014; Abraham, 2015; Caparole et al., 2015; Kang et al., 2015; Bouri et al., 2016; Ding et al., 2016; Ekong and Ebong, 2016; Gupta, 2016; Kang et al., 2016; Kayalar et al., 2016; Salisu, Isah and Raheem, 2019a; Salisu, Swaray and Oloko, 2019b). To this end, we contribute to the existing literature on predicting stock returns using crude oil prices with respect to major firms in Nigeria's oil and gas sector.[1] According to Babatunde et al. (2013), asset prices and, particularly, stock prices will be affected by crude oil prices, through the cash flows of oil-related firms in an oil exporting country, namely Nigeria. In line with Narayan and Sharma (2011), as well as, Narayan and Gupta (2014), we explore the in-sample predictability of stock returns using crude oil prices. We however challenge the findings of Welch and Goyal (2008) that it is difficult to find a variable that can predict stock returns out-of-sample.

In light of the aforementioned, our paper proffers answers to two important questions: (1) Do crude oil prices matter in the predictability of stock returns? In other words, does the inclusion of oil price in the traditional capital asset pricing model (CAPM) improve the accuracy of its stock returns forecast, and (2) Does accounting for asymmetries matter in the predictability of stock returns. Given that the superiority of any predictive model lies in its out-of-sample forecasts (Campbell, 2008), we evaluate and compare the in-sample and out-of-sample forecast performance of our hypothetical predictive models (that is, oil price-augmented CAPM and non-linear/asymmetric oil-based stock returns model) with the traditional CAPM and a linear/symmetric oil-based stock returns model, which are more restrictive. We achieve this using forecast evaluation tools including the root mean square error (RMSE) and the Campbell and Thompson test statistic (C-T test, subsequently). The in-sample forecast is conducted using 75% of the full sample data. The out-of-sample forecast, on the other hand, is based on three forecast horizons, namely, 4 months, 8 months and 12 months. We also support our arguments with predictability graphs for both the unrestricted and restricted predictive models in order to compare the fitted values of stock returns with their actual values.

The rest of the paper is structured as follows. Section two gives a brief review of the literature on the oil-stock nexus. Section three contains the methodology employed by this study. Section four entails data and preliminary analyses. Discussion of results is contained in Sections five, while Section six concludes the paper.

2. Review of the literature

2.1. Theoretical issues

Numerous studies on stock returns have deployed the asset pricing models in identifying the probable determinants of stock market indices, particularly stock prices and returns. The models cover various financial instruments such as equities, bonds, treasury bills and certificate among others. Unlike other asset classes, stocks are perceived to be highly risky. We therefore review the leading variants of the asset pricing models which include the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT).

Table 1
Data description and scope.

Variables	Start Period	End Period	No. of observations	75% of full sample
Crude oil prices (Brent and WTI)	January 2014	November 2019	71	53
Stock returns of listed oil and gas companies				
Conoil	January 2014	November 2019	71	53
Eterna	January 2014	November 2019	71	53
Forte	January 2014	November 2019	71	53
Japaul	January 2014	November 2019	71	53
Mobil	January 2014	November 2019	71	53
MRS	January 2014	November 2019	71	53
Oando	January 2014	November 2019	71	53
Seplat	April 2014	November 2019	68	51
Total	January 2014	November 2019	71	53

2.1.1. Capital asset pricing model

Capital asset pricing model (CAPM) remains the benchmark model among the competing asset pricing models that investors explore while attempting to evaluate the profitability of individual stocks (that is, company-specific stock returns). Developed by Sharpe (1964) and Lintner (1965), it is a framework through which investors select the portfolio of assets that would maximize the expected portfolio returns and minimize the associated risks. The model classifies risks into systematic and non-systematic risks. While the former is unavoidable but can be minimized, the latter can be avoided through different strategies, such as, hedging and portfolio diversification. Under the CAPM, expected returns on investment are a function of market returns, risk-free rate and a beta-factor. The beta-factor measures the systematic risk of an asset vis-à-vis the systematic risk of the market as whole. In other words, the beta factor shows the responsiveness of the returns of individual stocks to changes in the overall returns of the stock market.

2.1.2. Arbitrage pricing theory

The arbitrage pricing model (APT), which was introduced by Ross (1976), constitutes an alternative framework for asset pricing. Krause (2001) defined an arbitrage portfolio as a portfolio with no risk, no net investment, but a positive certain return. The arbitrage pricing model assumes that in equilibrium, no arbitrage possibility exists. Unlike CAPM, arbitrage pricing model is a multifactor model which allows for more than one beta factor. In this wise, the APT considers other sources of risk apart from the market risk, such as industry-specific factors. Unlike the CAPM, the arbitrage pricing theory accommodates both efficient and inefficient assets.

2.2. Empirical literature

A number of studies have investigated the determinants and/or the predictors of stock returns over the past decades and with reference to single-country and multi-country cases. We document a brief review of the empirical literature. Lewellen (2004) interrogated the extent to

[1] We acknowledge the existing literature in this respect (see, for instance, Narayan and Sharma, 2011; Narayan and Gupta, 2014; Sanusi and Ahmad, 2016; Soyemi et al., 2017; Swaray and Salisu (2018); Bagirov and Mateus, 2019; Zhu et al., 2019, among others).

Table 2
Preliminary analysis.

	Summary Statistics for the Variables						Autocorrelation Test		Heteroscedasticity Test	
	Mean	Std.	Skw	Kurt	J-B stat	CV	k = 4	k = 8	k = 4	k = 8
Full Sample for predictors: Crude oil prices and T-bill rate										
Brent	4.026	0.210	−0.528	3.129	2.779	5.216	7.906*	9.433	3.149**	1.601
WTI	3.949	0.182	−0.529	3.651	3.801	4.609	8.595*	10.72	0.113	0.282
TBR	12.20	3.647	−1.208	5.331	27.69***	29.89	3.808	4.784	0.873	0.427
Full Sample: Stock returns (*sr*)										
Conoil	0.951	0.117	0.749	3.411	5.939*	12.30	5.289	7.463	0.254	0.757
Eterna	1.098	0.479	0.518	2.357	3.653	43.62	2.743	13.06	2.634**	2.096*
Forte	0.914	0.130	0.047	2.428	0.827	14.22	3.479	5.625	0.563	0.425
Japaul	1.254	0.508	1.826	5.237	45.07***	40.51	0.782	1.845	3.724**	1.551
Mobil	1.007	0.061	0.061	3.226	3.895	6.058	8.323*	12.73	0.131	0.154
MRS	0.942	0.047	−0.589	2.752	3.566	4.989	4.704	8.995	1.073	0.832
Oando	0.901	0.231	0.062	2.473	0.648	25.64	1.479	2.596	1.246	0.789
Seplat	1.004	0.074	−0.352	2.194	2.674	7.371	4.224	7.434	0.298	0.349
Total	0.997	0.068	0.970	3.195	9.349***	6.820	3.921	7.198	0.304	0.306

Note: All variables except average Treasury bill rates and stock returns are in their log forms; Std is standard deviation, CV is coefficient of variation (defined as the standard deviation as percentage of mean), Skw is skewness, Kurt is Kurtosis, and J-B stands for Jarque-Bera. The test statistic has the null hypothesis of normality of variables. For autocorrelation and heteroscedasticity tests, the reported values are the Ljung-Box test Q-statistics for the former and the ARCH-LM test F-statistics in the case of the latter. We consider two different lag lengths (k) of 4 and 8 for robustness. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM test is that there is no conditional heteroscedasticity. ***, ** and * imply the rejection of all the null hypotheses at 1%, 5% and 10% levels of significance, respectively.

which financial ratios predict stock returns. The study showed that dividend yield predicts market returns during the period of 1946–2000, while during the period 1963–2000, book-to-market and earnings-price ratio perfectly predict returns. Looking beyond financial ratios as possible predictors of stock returns, Narayan and Sharma (2011) investigated the nexus between oil price and firm returns for 560 US firms quoted on the New York Stock Exchange. The study revealed that the performance of oil price on firm returns differs across sectors, whilst offering evidence on the lagged effect of oil price on firm returns.

In the same vein, Narayan and Gupta (2014) addressed the issue of whether oil price could predict stock returns for a century or not. Using a time-series data spanning 150 years, the study revealed that oil price predicts US stock returns, and the result is robust to in-sample and out-of-sample forecasts. The study also established that both negative and positive oil price changes played a significant role in predicting US stock returns, with negative oil price changes outperforming positive oil price changes. Furthermore, Sanusi and Ahmad (2016) modeled the determinants of stock returns using a multifactor asset pricing model with reference to the UK's oil and gas sector. Their results revealed that asset returns of the oil and gas firms quoted on the London Stock Exchange were significantly influenced by the market risk, oil price risk, size, as well as, the book-to-market related factors.

With the aid of Johansen cointegration approach, Adaramola (2012) explored the dynamic relationship between crude oil prices and Nigeria's stock market behaviour from 1985Q1 to 2009Q4. Empirical evidence showed that there is a significant short-run positive relationship between the two variables, while a negative impact of crude oil prices on stock was documented in the long run. Utilizing the Granger causality approach, the author also observed the existence of unilateral causality from crude oil prices to stock prices in Nigeria. Similarly, Babatunde et al. (2013) investigated the impact of oil price shocks on Nigeria's stock market performance over the period 1995Q1-2008Q4 using multivariate VAR approach. Findings revealed that stock returns respond with lags albeit negative reaction to oil price shocks even after controlling for other variables including industrial real GDP, interest rate and consumer price index. The study also failed to validate the existence of asymmetric relationship between oil price shocks and stock market returns in Nigeria.

Much related to our current paper is the study conducted by Ebechidi and Nduka (2017) regarding the impact of oil price shocks on energy sector stock returns in Nigeria using monthly data over the period from 2000 to 2015. By employing the GARCH approach, the authors found that in terms of returns series, there is a positive relationship between crude oil prices and energy stock returns. However, in volatility terms, stock returns of the energy sector exhibit a negative behaviour to changes in crude oil prices. Other significant drivers of energy stock returns include interest rate differential and exchange rate. Also in the case of Nigeria, Soyemi et al. (2017) examined the effect of oil price shock on stock returns of listed energy firms over the period of 2007–2014. Their study revealed that oil shocks has a direct positive relationship with company stock returns, while an indirect relationship exists between oil shocks and firm stock returns channeled through market returns.

Similarly, Zhu et al. (2019) investigated the effect of oil price volatility on stock returns of new energy firms in China. The study found heterogeneous performance of new energy firms with respect to oil prices. The study also revealed that while state-owned firms are more sensitive to asymmetric effect of oil price changes, the private-owned firms are highly responsive to negative oil price returns. In addition, Bagirov and Mateus (2019) examined the nexus between oil prices, stock markets and firm performance in Europe. The study observed the significant impact of crude oil prices on the performance of quoted oil and gas firms in Western Europe. Meanwhile, both the quoted and unquoted oil and gas firms' performances were negatively influenced by the geopolitical crisis in the region.

To this end, we differ from previous studies in the following distinct ways. Firstly, we explore a firm level analysis of the oil-stock nexus with respect to Nigeria's oil and gas sector. Secondly, our paper quantifies not only the responsiveness of stock returns of the major listed oil and gas companies in Nigeria to oil price movements, but also evaluates the predictability of stock returns using crude oil prices. Thirdly, unlike previous studies, we examine the role of crude oil prices in the predictability of stock returns within the framework of the Capital Asset Pricing Model (CAPM). Moreover, given that the earnings of oil and gas firms are highly exposed and sensitive to oil price movements (increases and decreases), we address the issue of whether accounting for asymmetries matter in the oil-stock nexus for the predictability of stock returns or not. In addition, we employ the estimation procedure of Lewellen (2004), as well as, Westerlund and Narayan (2012, 2015) to account for inherent properties in time-series data, such as, persistence, endogeneity and conditional heteroscedasticity effects.

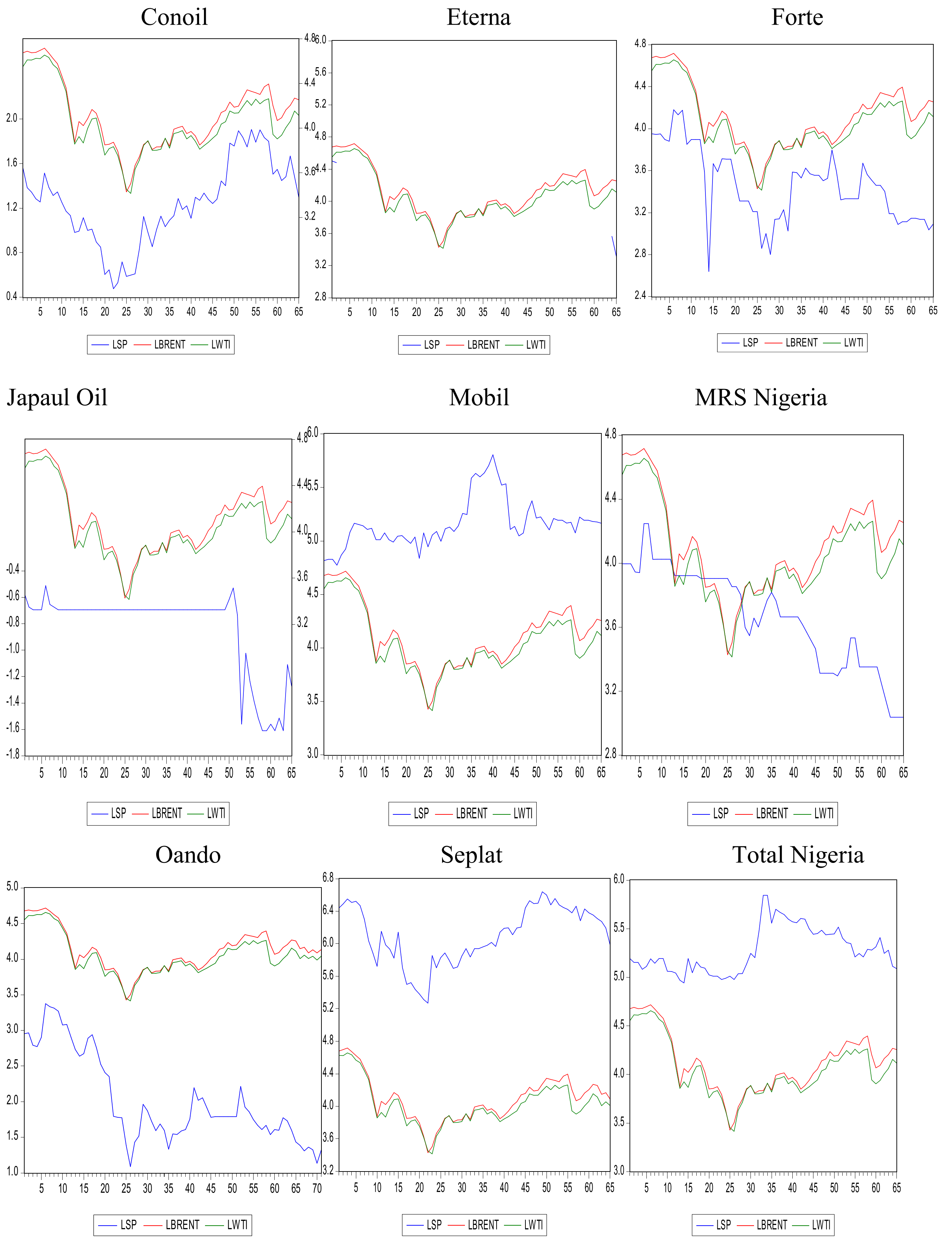

Fig. 1. Trends in stock prices and crude oil prices (Brent and WTI).

Table 3
Result of ADF unit root test.

Variable	Level			First Difference			I(d)
	A	B	C	A	B	C	
Crude oil prices and Treasury bill rate							
Brent	−2.025	−2.249	−0.602	−5.766***	−5.746***	−5.928***	I(1)
WTI	−2.146	−2.411	−0.692	−5.969***	−5.957***	−6.087***	I(1)
TBR	−4.554***	−4.580***	−0.731	–	–	–	I(0)
Stock returns (*sr*)							
Conoil	−2.786	−2.819*	0.101	–	–	–	I(0)
Eterna	−1.560	−1.846	−0.626	−8.223***	−8.146***	−8.229***	I(1)
Forte	−2.179	−2.456	−1.041	−8.402***	−8.231***	−8.229***	I(1)
Japaul	−2.669	−2.269	−0.988	−7.388***	−7.455***	−7.533***	I(1)
Mobil	−1.936	−1.947	−0.236	−8.726***	−8.807***	−8.893***	I(1)
MRS	−3.296*	−2.997**	−0.699	–	–	–	I(0)
Oando	−2.073	−2.019	−0.671	−8.382***	−8.449***	−8.529***	I(1)
Seplat	−1.037	−1.519	−0.098	−8.087***	−7.777***	−7.854***	I(1)
Total	−1.173	−1.619	0.035	−7.859***	−7.617***	−7.688***	I(1)

Note: ***, ** and * indicate the rejection of the null hypothesis of a unit root at 1%, 5% and 10%, respectively; A, B and C denote models with intercept and trend, with intercept only and with none, respectively; I(d) implies the order of integration, where d is the number of differencing required for a series to become stationary; Series that are stationary at levels do not require reporting their first differences.

Table 4
Persistence and endogeneity test results for predictors.

Company	Persistence			Endogeneity		
	Brent	*WTI*	*TBR*	*Brent*	*WTI*	*TBR*
Conoil	0.931***	0.924***	0.494***	0.046	0.011	−0.005
Eterna	0.931***	0.924***	0.494***	0.946	0.689	−0.014
Forte	0.931***	0.924***	0.494***	−0.172	−0.162	0.006
Japaul	0.931***	0.924***	0.494***	−0.803	−0.890	0.011
Mobil	0.931***	0.924***	0.494***	0.031	0.021	−0.002
MRS	0.931***	0.924***	0.494***	−0.095	−0.109	−0.0005
Oando	0.931***	0.924***	0.494***	0.134	0.007	−0.010
Seplat	0.911***	0.895***	0.496***	0.249**	0.133	−0.002
Total	0.914***	0.898***	0.495***	0.214**	0.118	−0.002

Note: ***, **, and * imply statistical significance of coefficients at 1%, 5%, and 10% levels of significance, respectively. This in turn indicates the absence of persistence effects and endogeneity bias in the predictors, which in this case are global crude oil prices (Brent and WTI) and T-bill rate.

3. Methodology

We consider the capital asset pricing model (CAPM) in this paper due to its suitability in explaining the stock behaviour of individual companies unlike other asset pricing models which have some aggregative dimension. For instance, Babatunde et al. (2013) considered the Fama's (1981) hypothesis which stipulates that the level of economic activity and inflation play a role in stock market behaviour. Other past studies with more focus on the Nigerian economy - Adaramola (2012), as well as, Ebechidi and Nduka (2017) – employed approaches that evaluate the responsiveness of aggregative stock market returns to changes in crude oil prices. With focus on major oil and gas companies that are listed on the Nigerian Stock Exchange (NSE), we hypothesize that augmenting the traditional CAPM (where the explicit explanatory variable is the returns on risk-free assets, such as, Treasury bills) using crude oil prices would improve the predictability of stock returns. This therefore yields the oil price-augmented CAPM as follows:

$$SR_t = \alpha + \gamma TR_t + \lambda op_t + \varepsilon_t \tag{1}$$

where SR_t is the year-on-year stock returns, obtained by taking the time derivatives of the natural log of a company's share prices over a lag of 12 months; TR_t is Treasury bill or T-bill rate, and op_t is the natural log of crude oil prices (details about the data utilized are provided in the next section).[2] The ε_t is zero mean idiosyncratic error term on stock returns and the coefficients γ and λ measure the respective impacts of T-bill rate and crude oil prices on stock returns. The underlying null hypothesis of no predictability is that $\gamma = \lambda = 0$.

In order to resolve any potential endogeneity bias resulting from the correlation between op_t and ε_t, as well as, any probable persistence effect, we utilize the approach of Lewellen (2004). The underlying predictive model that accounts for these effects can be specified as follows:

$$SR_t = \alpha + \gamma_{adj} TR_{t-1} + \delta(TR_t - \rho_0 TR_{t-1}) + \lambda_{adj} op_{t-1} + \theta(op_t - \rho_0 op_{t-1}) + \mu_t \tag{2}$$

where the parameters $\gamma_{adj} = \gamma - \delta(\rho - \rho_0)$ and $\lambda_{adj} = \lambda - \theta(\rho - \rho_0)$ are the bias adjusted ordinary least squares estimators of Lewellen (2004) which help to correct for any persistence effects in the predictive model. The additional terms $\delta(TR_t - \rho_0 TR_{t-1})$ and $\theta(op_t - \rho_0 op_{t-1})$ correct for any endogeneity bias resulting from the correlation between TR_t and μ_t, as well as, between op_t and μ_t. Accounting for endogeneity bias here is important since there could be several determinants of stock prices/returns which are suppressed in equation (1).[3] Moreover, to resolve the conditional heteroscedasticity effect, Westerlund and Narayan (2012, 2015) suggest pre-weighting all the data by $1/\widehat{\mu}_t$ and estimating the resulting equation with OLS. This modified OLS estimator is described as the Feasible Quasi-Generalized Least Squares (FGLS) estimator in Westerlund and Narayan (2012, 2015), and it is computed (we use the

[2] We utilize the year-on-year stock returns to suppress the impact of seasonal variations associated with the monthly share price data.

[3] Other possible determinants of stock returns from the extant literature include but not limited to industrial production, inflation and investor risk attitudes (see, for instance, Roll and Ross, 1980 and Chen et al., 1986).

Table 5
In-sample Predictability Results for stock returns using Traditional & Oil price-augmented CAPM.

Company	sr_t^{tr}	sr_t^{aug}					
		CASE I			CASE II		
	TBR	*Brent*	*TBR*	Redundancy test (t-stat)	*WTI*	*TBR*	Redundancy test (t-stat)
Conoil	0.002 (0.006)	**−0.212* (0.119)**	**0.009* (0.005)**	**1.776 [0.084]**	−0.222 (0.178)	0.009 (0.006)	1.251 [0.219]
Eterna	0.126*** (0.022)	0.123 (0.536)	0.164*** (0.028)	0.228 [0.821]	0.609 (0.599)	0.171*** (0.026)	1.018 [0.315]
Forte	−0.003 (0.004)	**0.949*** (0.193)**	**−0.011 (0.008)**	**4.917 [0.000]**	**0.896*** (0.215)**	**−0.019** (0.008)**	**4.173 [0.000]**
Japaul	−0.621*** (0.033)	**2.417** (1.083)**	**−0.666*** (0.049)**	**2.232 [0.032]**	**4.568*** (1.402)**	**−0.592*** (0.046)**	**3.259 [0.002]**
Mobil	0.019*** (0.004)	−0.147 (0.169)	0.009*** (0.002)	0.869 [0.390]	−0.188 (0.175)	0.011*** (0.003)	1.075 [0.289]
MRS	0.007*** (0.002)	0.068 (0.056)	0.002 (0.004)	1.224 [0.229]	0.081 (0.069)	0.003 (0.004)	1.164 [0.252]
Oando	0.007 (0.009)	0.296 (0.343)	0.023* (0.012)	0.863 [0.394]	0.236 (0.383)	0.019* (0.011)	0.615 [0.542]
Seplat	0.015*** (0.003)	**−0.184* (0.092)**	**0.009*** (0.003)**	**1.991 [0.054]**	**−0.193* (0.113)**	**0.010*** (0.002)**	**1.713 [0.095]**
Total	0.010*** (0.003)	0.041 (0.091)	0.010*** (0.002)	0.452 [0.654]	0.133 (0.102)	0.011*** (0.002)	1.297 [0.204]

Note: ***, ** and * implies the rejection of the null hypothesis of no predictability at 1%, 5% and 10% levels of significance. The values in parentheses are the standard errors associated with the first-order autoregressive coefficients in our predictive models (that is, traditional and oil price-augmented CAPM). The values in [ ] are probabilities associated with the t-test for the redundancy of variables. The null hypothesis of variable redundancy is rejected for all $p \leq 0.1$. Here, we consider 75% of the full sample data.

Table 6
In-sample and Out-of-sample forecast performance results for Traditional Capital Asset Pricing Model (CAPM) using RMSE.

Company	*TBR*			
	In-sample	Out-of-sample		
		$h=4$	$h=8$	$h=12$
Conoil	0.1185	0.1336	0.1500	0.1719
Eterna	0.4603	0.4556	0.5223	0.6285
Forte	0.1259	0.1207	0.1181	0.1228
Japaul	2.3520	2.2533	2.3797	2.3147
Mobil	0.0667	0.0707	0.0887	0.0936
MRS	0.0417	0.0405	0.0443	0.0445
Oando	0.2378	0.2412	0.2448	0.2578
Seplat	0.0596	0.0651	0.0876	0.1090
Total	0.0734	0.0898	0.1152	0.1496

Note: Capturing 75% of the full sample, we evaluate the in-sample and out-of-sample forecast performance (using 4, 8 and 12 months as the forecast horizons) of our predictive model, which in this case is the traditional CAPM with the aid of root mean square error (RMSE). The smaller the root mean square error (RMSE), the greater the predictive power of a model and vice versa.

example of crude oil price since it is our predictor variable of interest) as:

$$\gamma_{adj}^{FGLS} = \frac{\sum_{t=q_m+2}^{T} \tau_t^2\ op_{t-1}^d\ SR_t^d}{\sqrt{\sum_{t=q_m+2}^{T} \tau_t^2\ \left(op_{t-1}^d\right)^2}} \tag{3}$$

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

To account for asymmetries in the predictability of stock returns, we consider a bivariate model with crude oil price as the only predictor of stock returns as follows:

$$SR_t = \alpha + \lambda_{adj} op_{t-1} + \theta(op_t - \rho_0 op_{t-1}) + \mu_t \tag{4}$$

We then decompose crude oil prices (op_t) into positive (op_t^+) and negative (op_t^-) changes using the Shin et al. (2014) approach as follows:

$$op_t^+ = \sum_{k=1}^{t} \Delta op_k^+ = \sum_{k=1}^{t} \max(\Delta op_k, 0) \tag{5}$$

$$op_t^- = \sum_{k=1}^{t} \Delta op_k^- = \sum_{k=1}^{t} \min(\Delta op_k, 0) \tag{6}$$

Table 7
In-sample and Out-of-sample forecast performance results for Oil price-augmented CAPM using RMSE (Brent and WTI crude oil prices).

Company	*TBR & Brent*				*TBR & WTI*			
	In-sample	Out-of-sample			In-sample	Out-of-sample		
		$h=4$	$h=8$	$h=12$		$h=4$	$h=8$	$h=12$
Conoil	0.1092	0.1123	0.1231	0.1378	0.1084	0.1125	0.1304	0.1494
Eterna	0.5236	0.5045	0.5648	0.6279	0.5580	0.5399	0.5961	0.6499
Forte	0.1969	0.1989	0.1962	0.1909	0.1594	0.1626	0.1613	0.1630
Japaul	2.5910	2.4853	2.6262	2.5599	2.4432	2.3424	2.4054	2.3774
Mobil	0.0727	0.0713	0.0726	0.0721	0.0679	0.0671	0.0697	0.0682
MRS	0.0509	0.0491	0.0478	0.0501	0.0470	0.0450	0.0449	0.0459
Oando	0.1709	0.1794	0.1847	0.1992	0.1793	0.1854	0.1842	0.1979
Seplat	0.0505	0.0547	0.0891	0.1140	0.0536	0.0602	0.0981	0.1257
Total	0.0711	0.0870	0.1078	0.1412	0.0805	0.0999	0.1194	0.1521

Note: Capturing 75% of the full sample, we evaluate the in-sample and out-of-sample forecast performance (using 4, 8 and 12 months as the forecast horizons) of our predictive model, which in this case is the oil price-augmented CAPM (using Brent and WTI prices) with the aid of root mean square error (RMSE). The smaller the root mean square error (RMSE), the greater the predictive power of a model and vice versa.

Table 8
In-sample and Out-of-sample forecast performance results for Oil price-augmented CAPM versus Traditional CAPM using C-T test (Brent and WTI crude oil prices).

Company	$sr_t^{tr-Brent}$ versus sr_t^{tr}				sr_t^{tr-WTI} versus sr_t^{tr}			
	In-sample	Out-of-sample			In-sample	Out-of-sample		
		h = 4	h = 8	h = 12		h = 4	h = 8	h = 12
Conoil	**0.0788**	**0.1596**	**0.1793**	**0.1987**	**0.0854**	**0.1580**	**0.1311**	**0.1314**
Eterna	−0.1375	−0.1073	−0.0814	0.0010	−0.2123	−0.1850	−0.1414	−0.0340
Forte	−0.5643	−0.6480	−0.6609	−0.5544	−0.2662	−0.3469	−0.3652	−0.3274
Japaul	−0.1016	−0.1029	−0.1035	−0.1059	−0.0388	−0.0395	−0.0108	−0.0271
Mobil	−0.0903	−0.0071	**0.1817**	**0.2302**	−0.0172	**0.0514**	**0.2140**	**0.2712**
MRS	−0.2202	−0.2097	−0.0762	−0.1224	−0.1273	−0.1096	−0.0109	−0.0290
Oando	**0.2818**	**0.2561**	**0.2458**	**0.2271**	**0.2461**	**0.2317**	**0.2478**	**0.2322**
Seplat	**0.1526**	**0.1593**	−0.0166	−0.0455	**0.1014**	**0.0745**	−0.1197	−0.1524
Total	**0.0327**	**0.0305**	**0.0651**	**0.0566**	−0.0956	−0.1124	−0.0356	−0.0161

Note: The Campbell-Thompson (C-T) test statistics as used here compares the unrestricted model, which in this case is the oil price-augmented CAPM (using Brent and WTI prices) with the traditional CAPM, which constitutes the restricted model. Positive C-T stat implies that the oil price-augmented CAPM is preferred to the traditional CAPM in predicting stock returns using the in-sample data covering 75% of the full sample and the out-of-sample forecast horizons of 4, 8 and 12 months. The reverse is the case for a negative C-T stat.

The revised predictive model for stock returns is then specified as:

$$SR_t = \alpha + \lambda_{adj}{}^{+} op_{t-1}^{+} + \theta^{+}\left(op_t^{+} - \rho_0^{+} op_{t-1}^{+}\right) + \lambda_{adj}{}^{-} op_{t-1}^{-} + \theta^{-}\left(op_t^{-} - \rho_0^{-} op_{t-1}^{-}\right) + \mu_t \tag{7}$$

where op_t^+ and op_t^- are defined as positive and negative partial sum decompositions of crude oil price changes, respectively. Equation (7) captures the role of positive and negative changes in crude oil prices in the predictability of stock returns. Hence, the null hypotheses of no predictability for op_t^+ and op_t^-, respectively, imply that $op_t^+ = 0$ and $op_t^- = 0$.

In addition, we employ two measures to evaluate the in-sample and out-of-sample forecast performance of two sets of predictive models for stock returns; they are root mean square error (informal approach) and the formal test of Campbell (2008). The first category is the comparison between the oil-price augmented CAPM and the traditional CAPM, while the second category makes a comparison between asymmetric/non-linear and symmetric/linear oil-based stock returns models. The Campbell and Thompson test statistic is computed as $1 - (\widehat{RMSE}_1 / \widehat{RMSE}_0)$, where $\widehat{RMSE}_1$ and $\widehat{RMSE}_0$ are, respectively, the root mean square errors obtained from the unrestricted models (that is, oil-price augmented CAPM and asymmetric oil-based stock returns model) and the restricted models (that is, the traditional CAPM and the symmetric oil-based stock returns model), respectively. A positive value of the statistic implies that the unrestricted model outperforms the restricted model; otherwise, it does not.

4. Data and preliminary analyses

4.1. Data description and source

The variables employed in this paper are the share prices of the major oil and gas firms that are currently listed on the Nigerian Stock Exchange (NSE), which serves as a basis for the computation of stock returns for those companies.[4] This study focuses on the oil and gas companies due to the direct exposure of their corporate performance (earnings) to movements in global crude oil prices. The study utilizes the average primary market T-bill rates across the tenors of 3, 6 and 12 months as a proxy for the returns on the risk-free asset. We also employ two global oil price benchmarks, namely, the UK Brent and the US West Texas Intermediate (WTI) crude oil prices. Monthly data on the three variables were collected from various sources over the period of January 2014 to November 2019. The data on the end-period share prices for all the oil and gas companies were compiled from the NSE's database.[5] We obtain the data on primary market T-bill rates and on crude oil prices from the databases of the Central Bank of Nigeria (CBN) and the World Bank, respectively. In order to allow for out-of-sample forecasts, we employ only 75% of the full sample in the in-sample predictability analysis.[6] Table 1 presents the data scope and the corresponding number of observations.

4.2. Preliminary analysis results

4.2.1. Graphical representation

Fig. 1 depicts the direction of co-movement between the natural log of share prices and the natural log of global crude oil prices (Brent and WTI) over the full sample period for each of the major oil and gas companies listed on the NSE. We observe the existence of a positive co-movement between the two variables for Conoil, Eterna and Seplat. We, however, note a negative co-movement between share prices and global oil prices for Forte, Mobil, MRS, Oando and Total. Meanwhile, there is no significant co-movement between the two variables in the case of Japaul Oil. This could be partly due to the company's relative diversity of operations unlike other companies whose operations are largely limited to either upstream or downstream activities.[7] While Eterna and Seplat largely operate in Nigeria's upstream sector (oil and gas exploration and production), others including Conoil, Forte, Mobil, MRS Nigeria, Oando and Total Nigeria subsist mainly in the downstream oil and gas sector (refining and marketing activities).[8] Nonetheless, the variability in share price behaviour of these firms to global crude oil price changes makes it compelling the consideration of not only oil price

[4] The oil and gas firms includes Conoil Plc, Eterna Plc, Forte Oil Plc, Japaul Oil & Maritime Services Plc, Mobil (or 11) Plc, MRS Nigeria Plc, Oando Plc, Seplat Petroleum and Development Company Plc and Total Nigeria Plc. While Seplat is listed on the NSE's premium board, others occupy the mainboard list of the Nigerian Bourse. Also, all except Mobil and Total are indigenous companies. While Mobil is a subsidiary of the US′ Exxon Mobil, Total Nigeria is a multinational affiliate of France's Total SA.

[5] Seplat commenced trading on the NSE in April 2014, which automatically serves as the start date for our analysis of the company.

[6] There is no theoretical basis for partitioning of the entire data into 25%, 50% or 75%, according to Westerlund and Narayan (2012). The only intrinsic value of such attempt is to generate robustness for analysis.

[7] We however include Japaul Oil in our sample set in order to examine the direct and/or indirect exposure of its stock returns to global oil price changes, since its activities could be classified under the mid-stream oil and gas sector (which deals with the transportation of petroleum products).

[8] Refer to company information on Bloomberg via https://www.bloomberg.com/profile/company/.

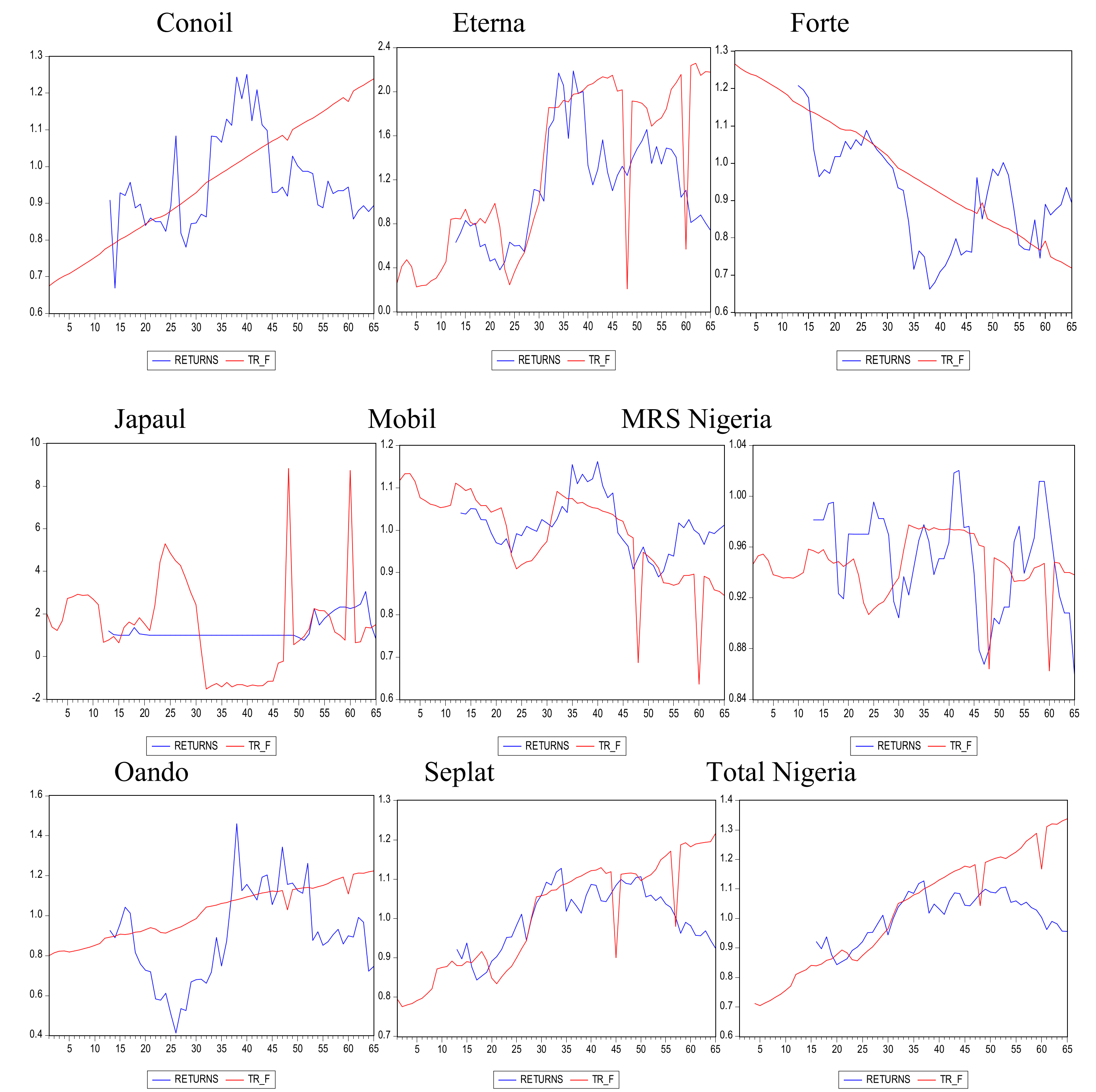

Fig. 2. Forecast graphs of Traditional CAPM (using Brent and WTI crude oil prices).

fluctuations, but also the direction of oil price movements (that is, positive and negative changes in oil prices) in the predictability of their respective stock returns. These are some of the issues addressed later in this paper. Our findings would serve as an eye-opener to the managements of the respective companies on the need to diversify their operation scope, so as to reduce the exposure of their corporate earnings to negative external shocks, such as, the crash in global oil prices that occurred between 2014 and 2016. In recent times, while crude oil prices (Brent and WTI) have failed to recover to its levels in 2014, stock returns have rather declined sharply for most of the major oil and gas companies that are currently listed on the NSE.

4.2.2. *Descriptive statistics*

Table 2 reports the summary statistics for global oil prices (Brent and WTI), average T-bill rates and the stock returns for the nine major oil and gas firms listed on the Nigerian Stock Exchange over the full sample period. Japaul Oil has the highest average stock returns, whereas Oando has the lowest average stock returns. With respect to coefficient of variation, average T-bill rates appear as the most volatile series among the predictors. While Eterna has the most volatile stock returns, the stock returns for Mobil were the least volatile. With respect to other statistical features of the series such as skewness, both global oil prices and average T-bill rates are positively skewed, while stock returns were positively skewed for all the companies except MRS Nigeria and Seplat. In terms of kurtosis, the results are mainly leptokurtic across the three predictors. The kurtosis statistics shows that stock returns are mainly platykurtic across the sample set with the exception of Conoil, Japaul Oil, Mobil and Total Nigeria. In addition, the Jarque-Bera statistic, that

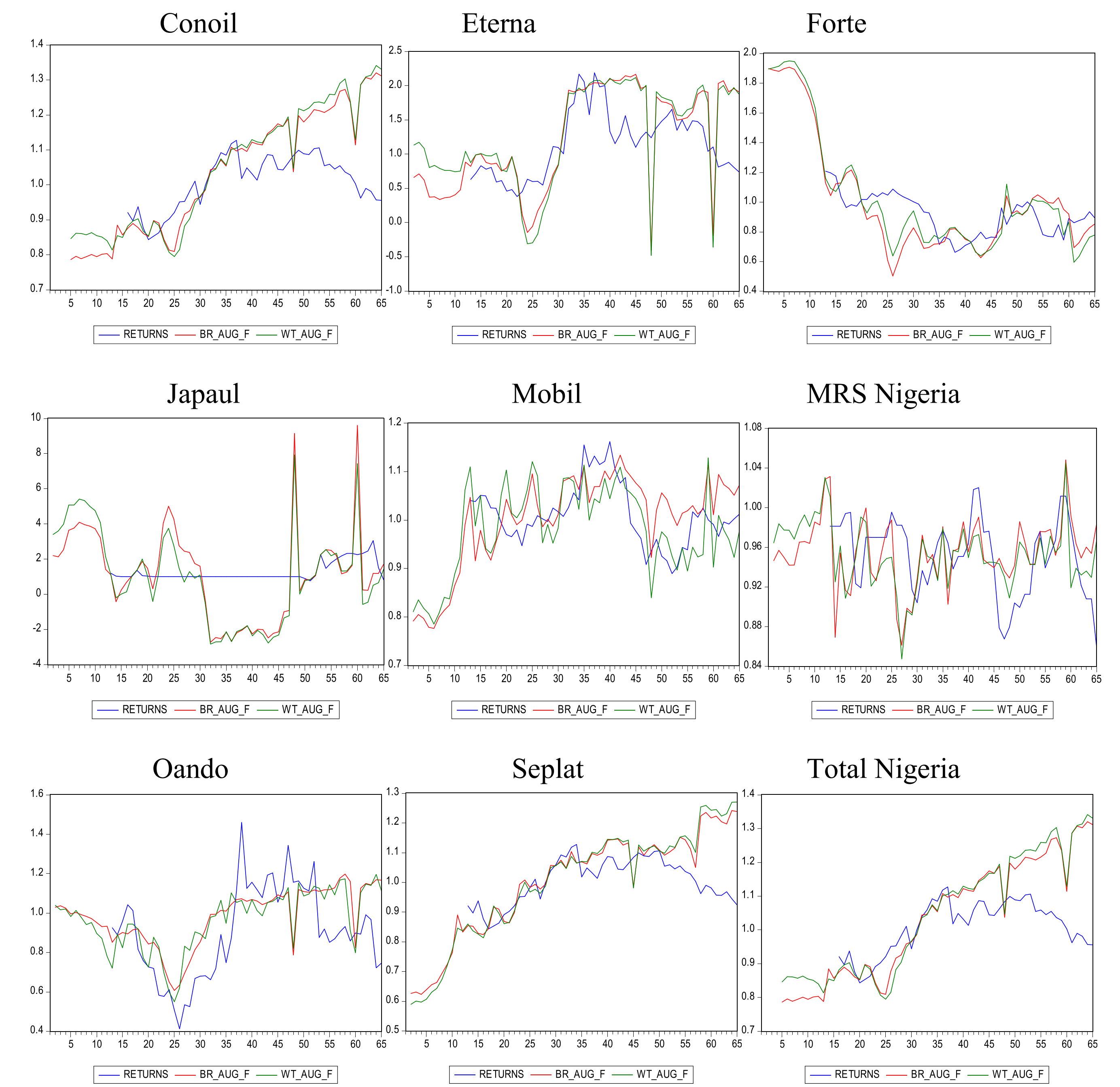

Fig. 3. Forecast graphs of Oil-price augmented CAPM (using Brent and WTI crude oil prices).

tests for normality using information from kurtosis and skewness, suggests non-normality for the average T-bill rates among the predictors. On the other hand, the test statistic indicates that stock returns follow normal distribution for all companies except Conoil, Japaul Oil and Total Nigeria.

4.2.3. Autocorrelation and conditional heteroscedasticity test results

Here, we conduct autocorrelation and conditional heteroscedasticity tests using Ljung-Box test Q-statistics and Autoregressive conditional heteroscedasticity lagrangian multiplier (ARCH-LM) test F-statistics, respectively (see Table 2 below). We consider two different lag lengths (k) of 4 and 8 for robustness. Our results show the presence of significant serial dependence at lower order for global crude oil prices. Meanwhile, there is no evidence of lower and higher serial correlation for average T-bill rates, as well as, stock returns for all the companies with the exception of Mobil. Similarly, we do not observe the presence of significant ARCH effects for all the predictors at both lower and higher orders except Brent crude oil price. Also, significant ARCH effects at both lower and higher orders are absent for the stock returns of all companies except Eterna and Japaul Oil. Our results generally show the absence of significant serial correlation and ARCH effects irrespective of the choice of lag lengths.

4.2.4. The unit root test result

We present the result of Augmented Dickey-Fuller (ADF) unit root test in Table 3. We consider the three ADF test regressions (that is, models with intercept and trend, intercept only, and none) in evaluating the stationary status of all the variables. Our result shows that among the predictors, only average T-bill rates is integrated of order zero; implying that it is stationary in levels and requires no differencing. However,

Table 9
In-sample Predictability Results for stock returns using Oil price-based stock model with asymmetries.

Company	sr_t^{asym}					
	Brent^{+}	*Brent*$^{-}$	Asymmetric test (t-stat)	*WTI*$^{+}$	*WTI*$^{-}$	Asymmetric test (t-stat)
Conoil	0.215* (0.113)	0.202* (0.114)	0.939[0.354]	0.086 (0.113)	0.078 (0.118)	0.521[0.605]
Eterna	**−1.259* (0.642)**	**−1.386** (0.649)**	**2.213[0.034]**	**−0.582 (0.709)**	**−0.699 (0.722)**	**1.853[0.072]**
Forte	0.783*** (0.158)	0.809*** (0.162)	−1.606[0.117]	0.926*** (0.188)	0.954*** (0.192)	−1.525[0.136]
Japaul	**1.595*** (0.441)**	**0.838* (0.445)**	**8.346[0.000]**	**−0.915* (0.466)**	**−1.482*** (0.537)**	**5.867[0.000]**
Mobil	0.115 (0.152)	0.116 (0.156)	−0.118[0.907]	0.386** (0.167)	0.392** (0.171)	−0.568[0.574]
MRS	**−0.096* (0.049)**	**−0.064 (0.046)**	**−3.415[0.002]**	**−0.060 (0.058)**	**−0.029 (0.060)**	**−3.767[0.001]**
Oando	**−0.347 (0.269)**	**−0.459 (0.274)**	**3.413[0.002]**	**−0.343 (0.378)**	**−0.439 (0.376)**	**1.799[0.081]**
Seplat	−0.331*** (0.093)	−0.338*** (0.089)	0.766[0.449]	−0.385*** (0.123)	−0.398*** (0.123)	1.203[0.237]
Total	**−0.233** (0.093)**	**−0.249** (0.093)**	**2.497[0.017]**	**−0.224** (0.108)**	**−0.237** (0.108)**	**1.964[0.058]**

Note: ***, ** and * implies the rejection of the null hypothesis of no predictability at 1%, 5% and 10% levels of significance. The values in parentheses are the standard errors associated with the first-order autoregressive coefficients in our predictive model (that is, asymmetric oil-based stock model). The values in [ ] are probabilities associated with the Wald test (t-test) for asymmetry. The null hypothesis of no asymmetry in the oil-stock nexus is rejected for all $p \leq 0.1$. Here, we consider 75% of the full sample data.

Table 10
In-sample and Out-of-sample forecast performance results for symmetric oil price-based stock returns model using RMSE (Brent and WTI crude oil prices).

Company	*Brent*				*WTI*			
	In-sample	Out-of-sample			In-sample	Out-of-sample		
		$h = 4$	$h = 8$	$h = 12$		$h = 4$	$h = 8$	$h = 12$
Conoil	0.1919	0.2430	0.2864	0.3278	0.1835	0.2234	0.2634	0.3015
Eterna	0.7607	0.8124	0.9401	1.1009	0.7759	0.8473	0.9757	1.1378
Forte	0.2116	0.2048	0.2013	0.1989	0.2036	0.1954	0.1977	0.2020
Japaul	1.6136	1.5482	1.5208	1.5052	5.0975	4.8753	4.8187	4.7552
Mobil	0.1175	0.1271	0.1326	0.1364	0.1268	0.1429	0.1488	0.1527
MRS	0.0517	0.0499	0.0499	0.0536	0.0474	0.0454	0.0461	0.0499
Oando	0.3693	0.3630	0.3625	0.3679	0.2461	0.2439	0.2442	0.2539
Seplat	0.0688	0.0729	0.1035	0.1284	0.0729	0.0846	0.1208	0.1493
Total	0.1189	0.1171	0.1139	0.1136	0.1214	0.1213	0.1192	0.1205

Note: Capturing 75% of the full sample, we evaluate the in-sample and out-of-sample forecast performance (using 4, 8 and 12 months as the forecast horizons) of our predictive model, which in this case is the symmetric oil-based stock model (using Brent and WTI prices) with the aid of root mean square error (RMSE). The smaller the root mean square error (RMSE), the greater the predictive power of a model and vice versa.

Table 11
In-sample and Out-of-sample forecast performance results for Oil price-based stock returns model accounting for asymmetries using RMSE (Brent and WTI crude oil prices).

Company	*Asym_Brent*				*Asym_WTI*			
	In-sample	Out-of-sample			In-sample	Out-of-sample		
		$h = 4$	$h = 8$	$h = 12$		$h = 4$	$h = 8$	$h = 12$
Conoil	0.1949	0.2495	0.3004	0.3394	0.1837	0.2237	0.2683	0.3028
Eterna	0.7355	0.7289	0.8154	1.0027	0.7337	0.7649	0.8804	1.0689
Forte	0.2159	0.2136	0.2069	0.2047	0.2182	0.2142	0.2112	0.2139
Japaul	0.7256	0.8284	0.8712	0.8547	0.7830	0.7799	0.7794	0.7880
Mobil	0.1188	0.1298	0.1361	0.1396	0.1322	0.1516	0.1581	0.1594
MRS	0.0470	0.0517	0.0521	0.0578	0.0369	0.0359	0.0429	0.0435
Oando	0.3947	0.3785	0.3679	0.3634	0.2461	0.2439	0.2442	0.2539
Seplat	0.0676	0.0692	0.0995	0.1223	0.0720	0.0818	0.1222	0.1489
Total	0.1090	0.1063	0.1051	0.1107	0.1186	0.1158	0.1132	0.1164

Note: Capturing 75% of the full sample, we evaluate the in-sample and out-of-sample forecast performance (using 4, 8 and 12 months as the forecast horizons) of our predictive model, which in this case is the asymmetric oil-based stock model (using Brent and WTI prices) with the aid of root mean square error (RMSE). The smaller the root mean square error (RMSE), the greater the predictive power of a model and vice versa.

global crude oil prices (Brent and WTI) are integrated of order one; implying that the variables are non-stationary in levels, but their first differences are stationary. Similarly, with the exception of Conoil and MRS Nigeria, we cannot reject the null of a unit root for the stock returns of all the major oil and gas companies.

4.2.5. Persistence and endogeneity test results

We further test for persistence and endogeneity effects in the predictors, which are global crude oil prices (Brent and WTI) and average T-bill rates in the present case, over the full sample period (see Table 4). This attempt is premised on the fact that the rejection of the null hypothesis of no unit root is not a sufficient condition to assume the absence of inherent persistence and endogeneity effects in the predictors. The persistence test has the null hypothesis of no persistence effect in the predictors. The coefficient of the AR(1) process [or the first-order autoregressive coefficient] was estimated for each predictor using OLS estimator and our results were found to be close or equal to one, which is often the features of series with higher order of integration,

Table 12
In-sample and Out-of-sample forecast performance results for Oil price-based stock returns model accounting for asymmetries versus symmetric model using C-T test (Brent and WTI crude oil prices).

Company	*Asym_Brent*				*Asym_WTI*			
	In-sample	Out-of-sample			In-sample	Out-of-sample		
		h = 4	h = 8	h = 12		h = 4	h = 8	h = 12
Conoil	**0.0224**	**0.0547**	**0.0355**	**0.0477**	−0.0017	−0.0041	−0.0197	−0.0043
Eterna	**0.0332**	**0.1028**	**0.1327**	**0.0892**	**0.0545**	**0.0973**	**0.0977**	**0.0605**
Forte	−0.0205	−0.0431	−0.0281	−0.0293	−0.0717	−0.0961	−0.0681	−0.0591
Japaul	**0.4841**	**0.3544**	**0.3123**	**0.3238**	**0.8319**	**0.8244**	**0.8216**	**0.8203**
Mobil	−0.0114	−0.0211	−0.0258	−0.0236	−0.0423	−0.0599	−0.0620	−0.0437
MRS	**0.0914**	−0.0345	−0.0425	−0.0777	**0.2204**	**0.2078**	**0.0674**	**0.1299**
Oando	−0.0686	−0.0425	−0.0150	0.0125	−0.2444	−0.2002	−0.1972	−0.1513
Seplat	**0.0180**	**0.0519**	**0.0387**	**0.0469**	**0.0120**	**0.0333**	−0.0108	**0.0026**
Total	**0.0833**	**0.0921**	**0.0771**	**0.0255**	**0.0232**	**0.0449**	**0.0507**	**0.0341**

Note: The Campbell-Thompson (C-T) test statistics as used here compares the unrestricted model, which in this case is the asymmetric oil-based stock model (using Brent and WTI prices) with the symmetric oil-based stock model, which constitutes the restricted model. Positive C-T stat implies that the asymmetric oil-based stock model is preferred to the symmetric oil-based stock model in predicting stock returns using the in-sample data covering 75% of the full sample and the out-of-sample forecast horizons of 4, 8 and 12 months. The reverse is the case for a negative C-T stat.

thus, suggesting that the predictors possess high level of persistency. With regards to the endogeneity test, we observe that all the three predictors are exogenous for the stock returns of all companies except Seplat and Total Nigeria. This, therefore, motivates our choice of estimator, developed by Lewellen (2004), which addresses the problem of any persistent and endogeneity effects in the predictors.

5. Discussion of results

5.1. Do crude oil prices matter in the predictability of stock returns?

5.1.1. In-sample predictability results

We observe mixed responsiveness of stock returns to movements in global oil prices across the major listed oil and gas companies in Nigeria (see Table 5). Irrespective of oil price measures, stock valuations of Forte and Japaul Oil are positively and significantly sensitive to oil price changes. We also observe a negative and significant responsiveness of stock returns to movements in the average T-bill rates, particularly for Japaul Oil. This is indicative of investors' preference shift towards risk-free assets (T-bills) from riskier stocks, given the strong positive relationship between oil prices and the firm's stock returns. However, stock valuations of Conoil and Seplat are negatively and significantly responsive to oil price movements, most especially in the case of Brent crude oil price. By implication, we can conclude that oil price fluctuations exert some significant influence on the stock performance of some oil and gas companies in Nigeria. Meanwhile, the insensitivity of stock returns to oil price movements for the majority of the listed oil and gas firms could be attributed to the absence of some factors, such as, the role of asymmetries in the oil-stock nexus. We take up this empirical exercise in later sections.

5.1.2. Forecast evaluation: oil-price augmented CAPM versus traditional CAPM

We further evaluate the forecast accuracy of our unrestricted predictive model, that is, oil price-augmented CAPM, in predicting firms' stock returns in relation to the benchmark restrictive model, that is, the traditional CAPM. Based on the RMSE and the C-T test statistic (see Tables 6–8), we observe that the oil price-augmented CAPM outperforms the traditional CAPM in the predictability of stock returns for Conoil and Oando using both in-sample and out-of-sample data and this result is robust to the choice of global oil price benchmarks (Brent and WTI). We also note the in-sample forecast superiority of our unrestricted predictive model over the benchmark restrictive model in the case of Seplat and Total. Similarly, we are able to validate the improvement in the out-of-sample forecast accuracy of our oil price-augmented CAPM over the traditional CAPM for Mobil. This result is robust to the choice of oil price measures. We further demonstrate graphically the relative superiority of predicting stock returns using the oil price-augmented CAPM over the traditional CAPM (compare Figs. 2 and 3). The predictability graphs make a comparison between the actual and predicted values of stock returns using both the traditional CAPM and the oil-price augmented CAPM.

5.2. Does accounting for asymmetries matter in the predictability of stock returns?

5.2.1. In-sample predictability results

From the previous results, we reveal that oil price matters in the predictability of at most four major oil and gas companies in Nigeria. Here, we further investigate if considering a role for non-linearities or asymmetries in the oil-stock nexus will improve the forecast accuracy of oil-based stock returns models (see Table 9). Consequently, we observe the significant responsiveness of stock returns to positive and negative changes in crude oil prices for Eterna, Japaul Oil, MRS Nigeria, Oando and Total.[9] This result is robust to the choice of global oil price benchmark (Brent and WTI). We also confirm the strong responsiveness of stock returns to positive changes in crude oil prices (Brent, most especially) for Japaul. This justifies the company's outstanding performance in terms of average stock returns over the full sample period (that is, January 2014 to November 2019) [see Table 2]. Meanwhile, stock returns are highly exposed and sensitive to negative changes in global oil prices (WTI in particular) for the aforementioned oil and gas companies except MRS Nigeria.

5.2.2. Forecast evaluation: asymmetric versus symmetric oil price-based stock returns model

Next, we evaluate and compare the forecast performance of our unrestricted predictive model, that is, oil-based stock model accounting for asymmetries, in predicting firms' stock returns in with the benchmark restrictive model, that is, the symmetric oil-based stock model. Based on the RMSE and the C-T test statistic (see Tables 10–12), we observe that our predictive stock model accounting for asymmetries outperforms the symmetric oil-based stock model in the predictability of stock returns for six major oil and gas companies in Nigeria, including

[9] Our result parallels the findings of Narayan and Sharma (2011), Sanusi and Ahmad (2016), Soyemi et al. (2017), Bagirov and Mateus (2019), Swaray and Salisu (2018), and Zhu et al. (2019).

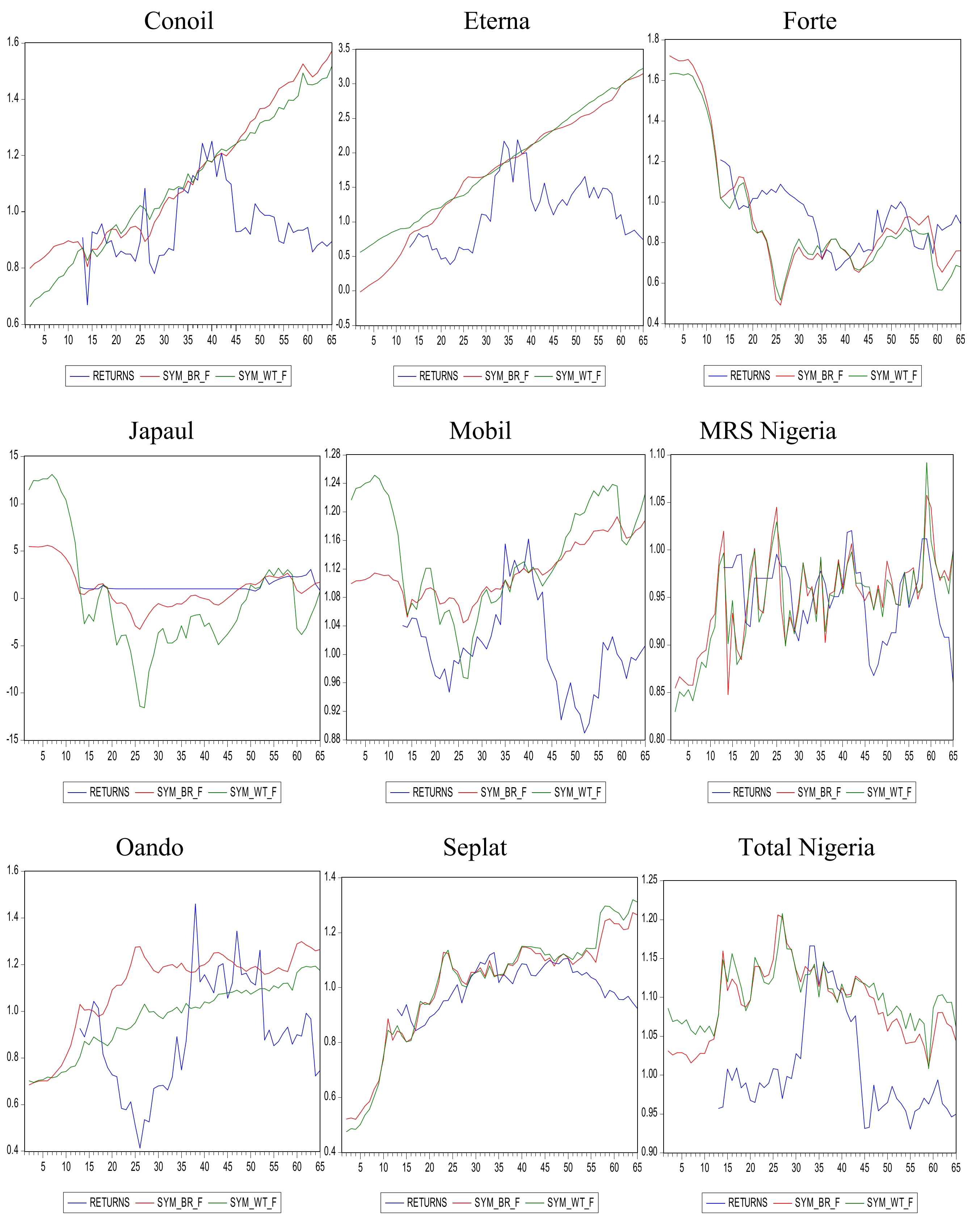

Fig. 4. Forecast graphs of symmetric oil-price-based stock returns model (using Brent and WTI crude oil prices).

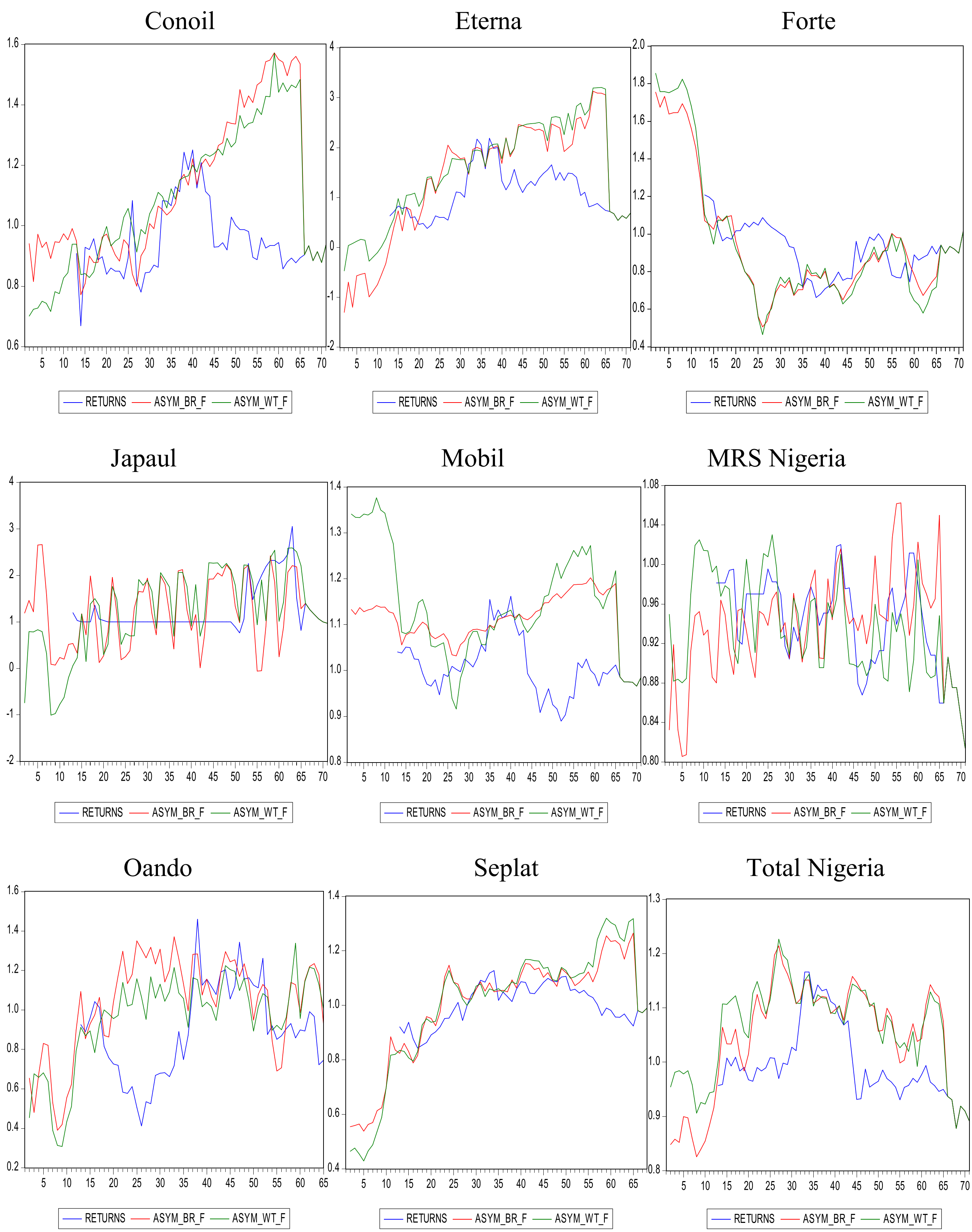

Fig. 5. Forecast graphs of asymmetric oil-price-based stock returns model (using Brent and WTI crude oil prices).

Conoil, Eterna, Japaul, MRS Nigeria, Seplat and Total Nigeria. Our result is robust to both in-sample and out-of-sample forecasts and to the choice of global oil price benchmarks (Brent and WTI).[10] We further show graphically the relative superiority of our asymmetric oil-based stock model in predicting stock returns over the symmetric oil-based model for stock returns (compare Figs. 4 and 5). The predictability graphs make a comparison between the actual and predicted values of stock returns using both the symmetric and asymmetric predictive models for stock returns.

6. Conclusion and implication of findings

The literature is replete with the nexus between aggregate stock market indices and crude oil prices, albeit mixed findings. We differ from the existing literature by exploring a firm-level analysis of Nigeria's oil and gas sector. We employ the share prices of nine major oil and gas companies that are currently listed on the Nigerian Stock Exchange over the period of January 2014 to November 2019. We also utilize two global oil price benchmarks (Brent and WTI crude oil prices) over a similar period. In order to resolve any potential persistence, endogeneity and ARCH effects in the predictors, we adopt the estimation procedure of Lewellen (2004), and Westerlund and Narayan (2012, 2015). Moreover, we evaluate and compare the in-sample and out-of-sample forecast performance of our unrestricted predictive models (which are the oil price-augmented CAPM and asymmetric oil-based stock model) with that of the benchmark restrictive models (which are the traditional CAPM and symmetric oil-based stock model) using the RMSE and the Campbell and Thompson test statistic.

Our results show significant in-sample predictability of stock returns using crude oil prices, thereby supporting the view that oil price matters in the predictability of stock returns for some oil and gas firms in Nigeria. We also offer evidence of the role of asymmetries in the predictability of stock returns of the majority of the listed oil and gas companies in Nigeria. This yields the conclusion that the direction of oil price movements (that is, positive and negative changes) matters in the valuation of oil and gas stocks in Nigeria. Overall, our results are robust to in-sample and out-of-sample forecasts as well as to the choice of global oil price benchmarks (Brent and WTI crude oil prices). Meanwhile, the increasing exposure of the earnings, and, by extension, the share prices of some major oil and gas companies to negative changes in global oil prices suggests the need for diversification of their scope of operations. This would not only mitigate the vulnerability of their corporate performance to unfavourable global oil shocks, but would also boost the confidence of investors in Nigeria's oil and gas stocks. While we acknowledge the recent CBN policy restricting local corporates and retail investors from the purchase of OMO (open market operations) bills, domestic and foreign investors are likely to be more strategic in the choice of their asset holdings, given that stock prices are highly volatile and the crash in T-bill yields to single-digits at both the primary and secondary markets following the policy pronouncement.

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[10] Our result negates the findings of Welch and Goyal (2008). We, however, affirm the previous findings of Narayan and Gupta (2014), Swaray and Salisu (2018), Salisu et al. (2019a), and Salisu et al. (2019b).