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A sectoral analysis of asymmetric nexus between oil and stock

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Abstract

This paper revisits the stock-oil price nexus. The extant literature has shown that the nexus can be situated around the multifactor asset pricing models to accentuate the role of oil price risks in stock valuation but with mixed findings. However, attempts to improve on previous studies in this pursuit led researchers to account for nonlinearities in the relationship to assess the asymmetric response of stock prices to positive and negative oil price changes. Consequently, we fit a predictive model for stock price that accounts for asymmetry on the basis of the predictive power of oil price shocks. Innovatively, we advance arguments for considering the importance of persistence, endogeneity and conditional heteroscedasticity inherent in the relationship and the data generating process for the in-sample and out-of-sample forecasting of US sectoral stock prices. Our results emphasise the role of oil price shocks and its asymmetric impacts in the in-sample predictability model of the sectoral stock prices. This evidence is also consistent for out-of-sample forecast evaluation and robust to changes in the measure of oil prices.

[1] The views expressed in this paper are those of the authors and do not in any way reflect the official position or thinking of the institutions to which they are affiliated.

Keywords: Sectoral stock prices, Oil Prices, The U.S. Asymmetry, Persistence, endogeneity and conditional heteroscedasticity.

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1.0 Introduction

Energy is central to the growth process of modern economies and hence the role of oil is pivotal in many sectors of economy (Zohrabyan, et al. 2014). Pioneering researches (for example Hamilton, 1983; Bernanke, 1983; Pindyck, 1991) on the impact of oil price on economic performance largely report negative effects of oil price increases on output and investment where uncertainty about the price of oil tends to distort investment (see Alsalman, 2016 for more). This has motivated research to study the influence of oil price changes in other facets of the economy given that oil prices impact financial variables as much as it does for real variables (see Sharma, 2017). In view of this, vagaries in the international oil market may pose challenges for firms' costs, profit and stock valuation and hence, create uncertainties for investors. To this end, we emphasize the understanding of the dynamics of oil price shocks and stock market fundamentals.

The modelling of the dynamics between oil and stock becomes relevant in the face of increased integration between financial and commodity markets. Thus, we consider the role of oil price shocks in the predictive model of stock prices. We further extend the previous studies to conduct a sectoral analysis in line with current trend in the literature. A study of this nature on the dynamics of oil price and stock market fundamentals across industries assists investors to adjust their portfolios and take advantage of investment opportunities in sectors revealed strong enough to hedge against oil risks. Although a study of this kind is relevant for both developing and developed economies given the pivotal role of oil in the economy, but it is more pertinent to large open economies like the United States where the domestic (financial and commodity) and international markets are more intertwined.

The asset pricing models; the single-factor models of Sharpe (1964) and Lintner (1965), the multi-factor models of Fama and French (1993) and the Arbitrage Theory of Capital Asset Pricing of Ross (1976) provide the theoretical basis for situating the model of stock prices to assess the impact of risk exposure on stock prices (see Narayan and Sharma, 2011; Phan, et al. 2015; Broadstock et al. 2016; Melichar, 2016; Sanusi and Ahmad, 2016; Salisu and Isah, 2017). These models, especially the multifactor models, allow for the inclusion of oil price shocks alongside traditional risk factors that could impact firms' future cash flows and hence, stock prices.

In the context of inverse relationship between oil price and economic performance previously highlighted, theory suggests inverse relationship between oil and stock prices. The thesis is that oil price affects stock price through the future cash flows (see Jones and Kaul, 1996; Hamilton, 2008). The argument follows that since oil is a crucial input in most firms' production, increases in oil prices enter the firms' cost of production to dampen profits and cash flows and then in turn have adverse effect on market value and stock prices (see Ramos and Veiga, 2013; Rafailidis and Katrakilidis, 2014; Cai, et al. 2017). Consequently, a host of studies indicate negative relationship between rising oil prices and stock prices (see Managi and Okimoto, 2013; Tsai, 2015; Ponka, 2016 for extensive review). Conversely, a number of studies also find no nexus between oil price and stock price (see for example Zohrabyan, et al. 2014; Alsalman, 2016). The absence of significant nexus can be theoretically linked to the ability of firms to hedge against fluctuations in oil prices and or to transfer the higher cost of oil to customers (see Hammoudeh, et al. 2010; Elyasiani, et al. 2011; Alsalman, 2016).

In the midst of these controversies, we attempt to improve on these studies to explore the inherent characteristics of the variables of interest. Thus, we account not only for asymmetry in the stock-oil nexus but also persistence, endogeneity and conditional heteroscedasticity. The case for considering asymmetry in the nexus emanates from the claim that stock returns react differently to demand and supply driven oil price shocks (see Kilian and Park, 2009). We discuss the motivation for asymmetry more extensively in the next section. To the best of our knowledge, our paper is the first to capture these peculiarities to further deepen our understanding of the oil price-stock market linkage using sectoral data . Our motivation for considering the role of persistence in the nexus stems from the argument that high frequency predictors such as oil price exhibits high persistence and conditional heteroscedasticity effects (see Narayan and Narayan, 2007; Salisu and Fasanya, 2013). Further empirical validation is found in Huang, et al. (2017) who show the presence of persistent asymmetric effect of oil price on the stock market across time scales. However, the study did not account for other data peculiarities nor is it a sectoral analysis.

We evaluate the predictability of the asymmetric stock models for the in-sample and out-of-sample forecast evaluation to support our claim of asymmetry in the oil-stock modelling. For this purpose, we follow the approach of Lewellen [LW hereafter] (2004) and Westerlund and Narayan [WN hereafter] (2012, 2014) to analyse the predictive model for the oil-stock price nexus. This framework allows us to simultaneously capture potential endogeneity, persistence effects and conditional heteroscedasticity effect in the predictive model. As demonstrated by LW (2004) and WN (2014), ignoring such effects in a predictive stock price model may bias the forecast results. This approach has also been used in the cases of different predictors to analyse the predictive model for stock price (see Narayan and Gupta, 2014; Narayan and Sharma, 2014;

Bannigidadmath and Narayan, 2015; Narayan and Bannigidadmath, 2015; Devpura et al., 2017; Salisu et al., 2017).

The rest of the paper is structured as follows: Section 2 justifies the need to account for asymmetry in oil-stock nexus. Section 3 provides the model set up including the forecast performance measures. Section 4 deals with data and preliminary analysis. In Section 5, we present and discuss the results while Section 6 concludes the paper.

2.0 A review of the literature on sectoral analyses of oil-stock nexus

Empirical exercises inquiring into the oil–stock price nexus for predicting aggregate stock price is not new (see Cunado and Perez de Gracia, 2014; Fang and You, 2014; Salisu and Isah, 2017; Sharma, 2017 for the review of studies based on aggregate stock prices). What is however relatively new is the sectoral analysis of the stock market prices (see for example Mohanty, et al. 2010; Mohanty and Nandha, 2011; Aggarwal, et al. 2012; Scholtens and Yurtseve, 2012; Degiannakis, et al. 2013; Broadstock and Filis, 2014; Bouri, et al. 2016; Singhal and Ghosh, 2016; Moreno et al. 2017) to allow for distinctive treatment of each sector and circumvent aggregation bias. However, these studies are mixed in terms of scope, oil proxy (either Brent or WTI), the methodology and findings. Further, this strand of the literature approach the inquiry by taking the relationship between oil price shock and stock returns to be direct, linear, and monotonic.

For instance, with focus on US transport companies, Aggarwal, et al. (2012) find that the firms' stock returns are influenced negatively by oil price increases. In the same vein, Moreno et al. (2017) obtain negative long-run relation between gas prices and stock market price in Spanish metallurgical firms. In other parlance, Bouri, et al. (2016) rely on the ARMAX-EGARCH method to show that the influence of world oil price is not uniform across the sectoral stocks (see also Scholtens and Yurtseve, 2012; Degiannakis, et al. 2013; Broadstock and Filis, 2014 for the same finding); with significant impact on financial and services sectors but less-important influence on the industrial sector. Previously, Mohanty et al. (2010) suggest that oil price shocks have no significant impact on oil and gas industry returns in the CEE countries over the full sample period but vary across firms in the sub-period analysis. More relatedly, Mohanty and Nandha (2011) also find that oil price exposures of firms in the US transportation sector vary across firms and over time. These empirical evidences lend credence to the distinctive study of sectoral analysis of stock markets.

The other strand of the literature relevant to the present study assesses the role of asymmetry in the oil-stock price nexus. Studies have shown that the price of oil is driven by different demand and supply shock (see Kilian, 2009; Kilian and Park, 2009). These arguments suggest that the oil-stock nexus is non-monotonous. A host of sectoral studies like the present one (for example Nanha and Brooks, 2009; Mohanty et al. 2013; Broadstock, et al. 2014; Tsai, 2015; Sanusi and Ahmad, 2016; Pinho and Madaleno, 2016; Trabelsi, 2017; Salisu and Isah, 2017) affirm asymmetry in the relationship between oil prices and equity prices. These studies broadly suggest asymmetric responses of sectoral stock prices to oil price changes and different transmission impacts depending on the sector analysed. Other set of studies suggest weak/limited evidence of asymmetric effects of oil price shocks (for example Zhang and Cao, 2013; Ponka, 2016; Li, et al. 2017). Further and more significantly, Huang et al. (2017) find evidence that oil price could exert persistent asymmetric effects on the stock market across time horizons. We therefore build on this direction to provide further information on the stock-oil nexus viz-a-viz the controversies in the literature.

3.0 The Model and Estimation Procedure

3.1 The Model

The predictive model for oil-stock nexus follows the Narayan and Gupta [NG hereafter] (2014) and Narayan and Bannigidadmath (2015) which captures oil price as a predictor of stock price as expressed below:

$$s_t = \alpha + \beta_1 p_{t-1} + \beta_2 \left(p_t - \gamma p_{t-1} \right) + \xi_t \qquad (1)$$

where s_t is the log of stock price and p_t is the log of oil price. The null hypothesis of no predictability is that $H_0: \beta_1 = 0$. On the basis of the theoretical relationship, a positive relationship is hypothesized between the two variables. The equation (1) essentially incorporates two terms: $\beta_1 p_{t-1}$ and $\beta_2 \left(p_t - \gamma p_{t-1} \right)$. The first term $\left(\beta_1 p_{t-1} \right)$ captures the conventional bi-variate predictive model [which can be expressed as $s_t = \phi + \delta p_{t-1} + \varepsilon_t$ in the absence of the second term. However, the inclusion of the second term $\left[\beta_2 \left(p_t - \gamma p_{t-1} \right) \right]$ is motivated by the work of Lewellen [LW hereafter] (2004) which demonstrates that such modifications to the conventional predictive model account for any inherent persistence effect in the model. Meanwhile, when dealing with high frequency predictors such as oil price, there is possibility of high persistence effects (see Narayan and Narayan, 2007; Salisu and Fasanya, 2013). To test for the presence of persistence, the following model is estimated with the Ordinary Least Squares (OLS) method (see also NG, 2014):

$$p_t = \varphi(1-\rho) + \rho p_{t-1} + \upsilon_t \text{ where } \upsilon_t \sim N\left(0, \sigma_\upsilon^2\right) \qquad (2)$$

The null hypothesis of no persistence - $H_0: \rho = 0$ is tested against the alternative hypothesis of the presence of persistence - $H_1: \rho \neq 0$. The degree of persistence is measured by ρ. This approach is preferred to the unit root test as the absence of unit root does not necessarily suggest the absence of persistence (LW, 2004 and WN, 2014).

This can be verified by regressing the residuals from the augmented predictive model (as in equation (1)) on the residuals from the persistence model (as in equation (2)); that is:

$$\hat{\varepsilon}_t = \eta\hat{\upsilon}_t + \xi_t \qquad (3)$$

The null hypothesis of no endogeneity - $H_0 : \eta = 0$ is tested against the alternative hypothesis of the presence of endogeneity - $H_1 : \eta \neq 0$. If we re-arrange the endogeneity equation after substituting $\upsilon_t = p_t - \varphi(1-\rho) - \rho p_{t-1}$ and $\varepsilon_t = s_t - \phi - \delta p_{t-1}$ gives a predictive model expressed in equation (1) where $\alpha = \phi + \eta\varphi(1-\delta)$. Thus, the equation already assumes the presence of persistence effects and therefore in the absence of same, equation (1) reduces to the traditional predictive model where $s_t = \phi + \delta p_{t-1} + \varepsilon_t$. Consequently, pre-testing the series for persistence becomes inevitable in order to determine the validity of the predictive model for forecasting purpose.

Recently, the work of WN (2014) shows that it may necessary to allow for conditional heteroscedasticity effect in equation (1) when dealing with high frequency predictors which tend to exhibit this effect. Like the persistence effect, a pre-condition for such consideration is to test whether there is presence of conditional heteroscedasticity using the ARCH-LM test, for instance, involving the variance test equation $\hat{\varepsilon}_t^2 = \psi + \lambda_1\hat{\varepsilon}_{t-1}^2 + \lambda_2\hat{\varepsilon}_{t-2}^2 + \cdots + \lambda_q\hat{\varepsilon}_{t-q}^2$ with the null hypothesis of no ARCH effect $H_0 : \lambda_1 = \lambda_2 = \cdots = \lambda_q = 0$ against the alternative hypothesis of the presence of ARCH effect $H_1 : \lambda_1 \neq \lambda_2 \neq \cdots \neq \lambda_q \neq 0$.

Thus, rather than estimating equation (1) with OLS, WN (2014) propose a Feasible Quasi Generalized Least Squares (FQGLS) estimator as an alternative estimator which allows the model to exploit any information inherent in the conditional heteroscedasticity effect. The FQGLS estimator assumes the regression error, that is ξ_t, follows an autoregressive conditional heteroskedastic (ARCH) structure - $\hat{\sigma}^2_{\xi,t} = \psi + \sum_{i=1}^{q} \psi_i \hat{\xi}^2_{t-i}$, and the resulting $\hat{\sigma}^2_{\xi,t}$ can be used as a weight in the predictive model (see also Narayan and Gupta, 2014; Bannigidadmath and Narayan, 2015; Narayan and Bannigidadmath, 2015; Devpura et al., 2017). The estimation of the weighted predictive model by OLS is described as the FQGLS estimator. Thus, the estimator can be described as a GLS-based t-statistic for testing $\beta_1 = 0$ is given as:

$$t_{FQGLS} = \frac{\sum_{t=q_m+2}^{T} \tau_t^2 p_{t-1}^d s_t^d}{\sqrt{\sum_{t=q_m+2}^{T} \tau_t^2 \left(p_{t-1}^d\right)^2}} \tag{4}$$

where $\tau_t = 1/\sigma_{\xi,t}$ is used in weighting all the data in the predictive model and $p_t^d = p_t - \sum_{i=2}^{T} p_t / T$. As previously mentioned, the asymmetric version of equation (1) is partitioned into two for positive and negative changes in oil price as given below:

$$s_t = \alpha^+ + \beta_1^+ p_{t-1}^+ + \beta_2^+ \left(p_t^+ - \rho^+ p_{t-1}^+\right) + \xi_t^+ \tag{5a}$$

$$s_t = \alpha^- + \beta_1^- p_{t-1}^- + \beta_2^- \left(p_t^- - \rho^- p_{t-1}^-\right) + \xi_t^- \tag{5b}$$

where p_t^+ and p_t^- denote the positive and negative oil prices respectively. In essence, equation (1) is the predictive model of stock price with a symmetric oil price while equations (5a) and (5b) represent the asymmetric variants. The computation of p_t^+ and p_t^- follows the Shin et al. (2014) approach as given below:[2]

$$p_t^+ = \sum_{k=1}^{t} \Delta p_{ik}^+ = \sum_{k=1}^{t} \max(\Delta p_{ik}, 0) \tag{6a}$$

$$p_t^- = \sum_{k=1}^{t} \Delta p_{ik}^- = \sum_{k=1}^{t} \min(\Delta p_{ik}, 0) \tag{6b}$$

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[2] This approach was used by Swaray and Salisu (2017) and Salisu and Isah (2017) in the analyses of oil-stock nexus

where equations (6a) and (6b) denote positive and negative partial sum decompositions of oil price changes respectively. There is evidence of asymmetry, if the coefficients of p_t^+ and p_t^- are statistically different from each other; otherwise their effect on stock market is considered identical.

3.2 Forecast Evaluation

The forecast evaluation is carried out for both the in-sample and out-of-sample periods. We use the 50 percent observations of the full-sample for the forecast evaluation and the rolling window approach[3] which accounts for the time-varying behavior in the oil-stock nexus is employed to produce the forecast results. We start with the in-sample evaluation which involves testing for the predictability of oil price in the stock price model for both the symmetric and asymmetric variants using the GLS-based t-statistic as well as the Root Mean Square Error (RMSE). As conventional in time series forecasting, we also estimate first order $\left(s_t = \alpha + \rho s_{t-1} + \upsilon_t\right)$ and second order $\left(s_t = \alpha + \rho_1 s_{t-1} + \rho_2 s_{t-2} + \upsilon_t\right)$ autoregressive models and thereafter we compare their forecast results with those obtained from the symmetric predictive model using the Campbell-Thompson (C-T hereafter) test[4] and Diebold-Mariano (D-M) test[5]. The C-T test is described as $R^2\left(OOS\_R\right)$ statistic where $OOS\_R = 1 - \left(\widehat{MSE}_1 / \widehat{MSE}_0\right)$. The $\widehat{MSE}_1$ and $\widehat{MSE}_0$ are the mean square error (*MSE*) of the prediction from the unrestricted and restricted models, respectively. The restricted model in this case is the autoregressive model while the unrestricted version is the symmetric model. A positive value of the

[3]This approach has also been used by Narayan and Gupta (2014), Bannigidadmath and Narayan (2016) and Salisu et al. (2017).

[4]See Campbell and Thompson (2008).

[5]See Diebold and Mariano (1995).

statistic i.e. $OOS\_R > 0$ suggests that the unrestricted model outperforms the restricted model; otherwise, it does not.

Also, the D-M test is used to test for the equality of forecast accuracy of two forecasts (in this case between the autoregressive model and the symmetric model). The test is given as:

$$\text{D-M stat} = \frac{\bar{d}}{\sqrt{\frac{1}{T}V(d)}} \sim N(0,1) \tag{7}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T}\left[g(\xi_{it}) - g(\xi_{jt})\right]$ is the sample mean loss differential and $V(d)$ is the unconditional variance of d. The $\{\xi_{it}\}_{t=1}^{T}$ and $\{\xi_{jt}\}_{t=1}^{T}$ are the forecast errors associated with the two forecasts say $\{\hat{y}_{it}\}_{t=1}^{T}$ and $\{\hat{y}_{jt}\}_{t=1}^{T}$ respectively. The $g(\xi_{it})$ and $g(\xi_{jt})$ are the loss functions associated with these two forecasts while $d_t \equiv g(\xi_{it}) - g(\xi_{jt})$ is the loss differential. The null hypothesis of equal forecast accuracy for two forecasts is that $E[d_t] = 0$. Thus, the forecast accuracy of the symmetric and autoregressive models is considered relatively equal if the null hypothesis of the D-M test is not rejected; otherwise, it is not.

Also, the D-M test is extended to the asymmetric variants both for the in-sample and out-of-sample forecasts in order to test whether the forecast accuracy of positive and negative changes in oil price is equal. In the literature, the forecast combination approach has also been found to improve forecast results (see Timmermann, 2013 for a review). Thus, we also consider this approach to test whether combining the forecasts of positive and negative changes in oil price will enhance individual forecasts. We consider a simple average of the forecast results of both the positive and negative changes with the individual. The Combined forecast $f\left(\hat{f}_1, \hat{f}_2\right)$ is assumed to dominate individual forecasts $\hat{f}_1$ and $\hat{f}_2$ if $E\left[L\left(\hat{f}_i, y_{T+h}\right)\right] > \min E\left[L\left(f\left(\hat{f}_1, \hat{f}_2\right), y_{T+h}\right)\right]$, for $i = 1, 2$. (Timmermann, 2013).[6]

4.0 Data and Preliminary Analyses

This study relies on monthly data of US stock prices in all economic sectors and the world oil prices taking Brent and WTI spot prices as proxies. The historical data ranges from periods as presented on Table 1, it can be observed that unlike the sector stock prices, both oil prices have 335 observation, two last months of the series are unavailable as of the time of data collection. Apart from the real estate sector, other sectors have 337 observations spanning from September 1989 to September 2017[7]. Meanwhile the aggregate stock price runs from December 1927 to September 2017 making 1078 observations.

Table 1: Frequency Table

Variables	Start Date	End Date	Obs.
Oil Price			
Brent	09/1989	07/2017	335
WTI	09/1989	07/2017	335
Stock Price			
Aggregate	30/12/1927	05/09/2017	1078
Financial Sector	29/09/1989	05/09/2017	337
Info Tech Sector	29/09/1989	05/09/2017	337
Industry Sector	29/09/1989	05/09/2017	337
Energy Sector	29/09/1989	05/09/2017	337
Telecom Sector	29/09/1989	05/09/2017	337
Material Sector	29/09/1989	05/09/2017	337
Consumer Staples	29/09/1989	05/09/2017	337
Health Sector	29/09/1989	05/09/2017	337

[6] The forecast evaluation procedure adopted here is similar to the work of Salisu and Ndako (2017) involving the analyses of the nexus between stock price and exchange rate.

[7] This accounts for the reason why the sector is omitted from our estimation.

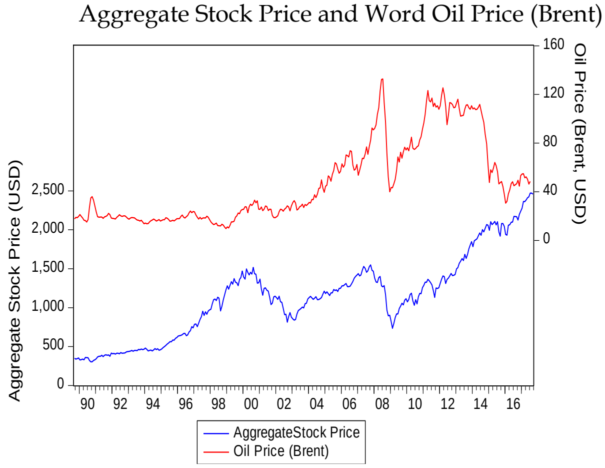
Consumer Disc Sector	29/09/1989	05/09/2017	337
Utilities Sector	29/09/1989	05/09/2017	337

Source: Authors' computations

Traditionally, it is important to explore the historical information derivable from the series through graphical illustrations; this will allow us some insights into their proper handling, understanding of possible co-movements and detection of likely responses to economic shocks. In Figure 1, aggregate stock price for all sectors is plotted against oil prices (Brent and WTI), an inverse relationship is observable between the periods of 1989 to 1999 after which both series seemed to respond to the US. Technology bubble bust, a cause of recession reflected by the sharp decrease in stock price and a sluggish decline in oil prices. Although the US economy picked up a little while after, aggregate stock price and oil prices took a rather positive relationship evidenced by the co movement from 2002. Meanwhile, a sharp decline in both series responding to the global recession of 2008 is discernible, recoveries in both series followed immediately. Despite oil prices crashing due to glut after 2012, aggregate stock price was less responsive to the glut and fall in oil prices around this period.

Fig. 1 Aggregate Stock Price and Oil Prices

Aggregate Stock Price and Word Oil Price (Brent)



Aggregate Stock Price and Word Oil Price (WTI)

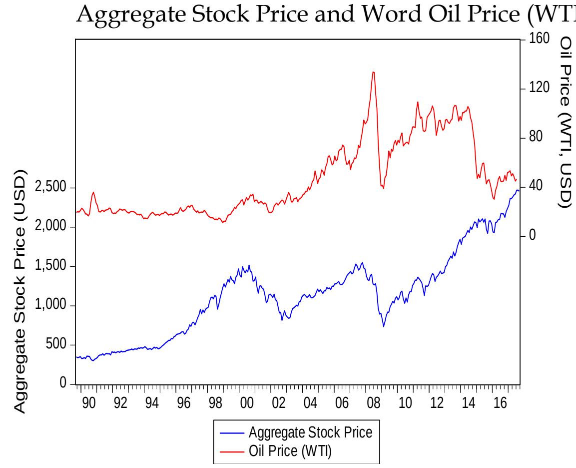
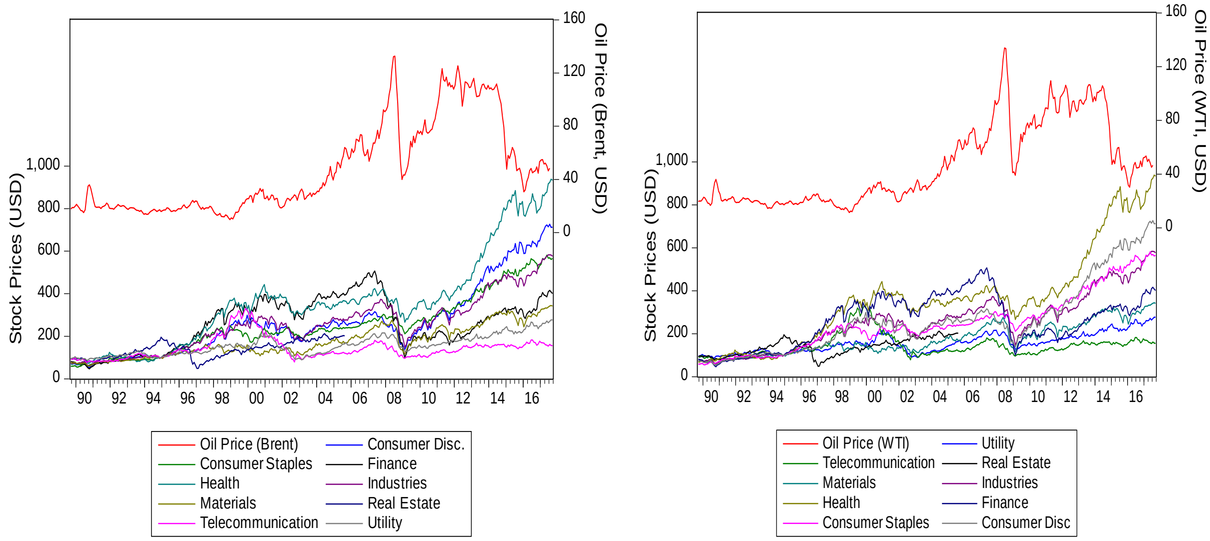


Fig. 2 Stock Prices and Oil Prices

Stock Prices and World oil Price (Brent) Stock Prices and World oil Price (WTI)



In Figure 2, all sectors' stock prices are plotted against oil prices (Brent and WTI) and a near perfect co-movement is evident, only that adjustment in stock returns preceded adjustments in oil prices. Expectedly, the oil glut induced sharp decline in oil prices is once again not reflected in the stock prices, just as in the aggregates. Meanwhile, two sectors, namely energy and information technology, exhibit patterns differing from other sectors, the two series spike in a way that may suppress information derivable from other sectors' series, a reason why they are plotted separately in Figures 3 and 4.

The spikes in energy stock price match that of oil prices in Figure 3 unlike other sectors in Figure 2, where stock prices adjustments preceded oil prices adjustments. This interesting co-movement is of no surprise, oil prices dominate world energy prices as oil is still the most sought after, changes in energy stock prices will necessarily resemble changes in oil price. Also, the technology bubble bust is now clearly represented in figure 4, as the spike in information technology sector stock price represents a period of technological price peak after which a turbulent decline was experienced. The remaining periods simply follow other sectors' pattern.

Fig. 3 Energy Stock Price and Oil Prices

Energy Stock Price and Word Oil Price (Brent) Energy Stock Price and Word Oil Price (WTI)

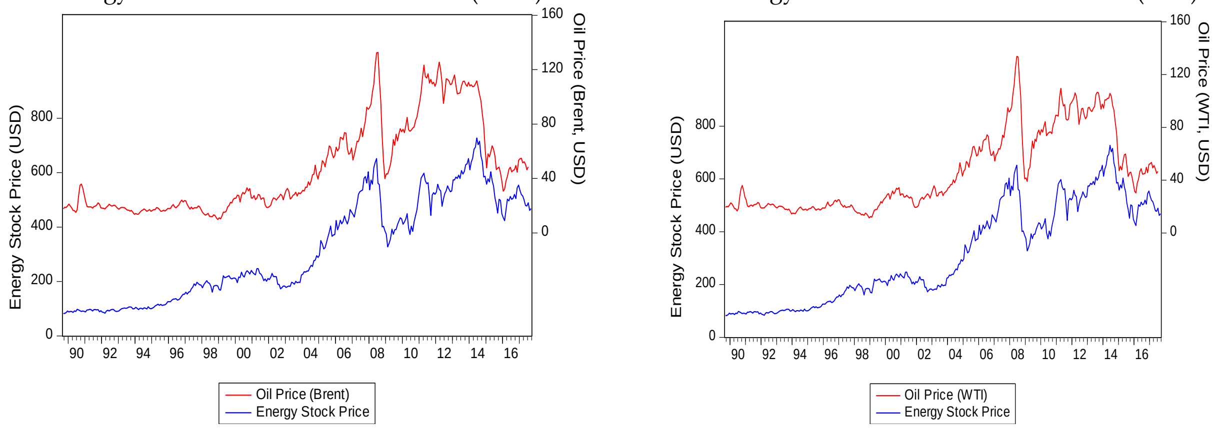
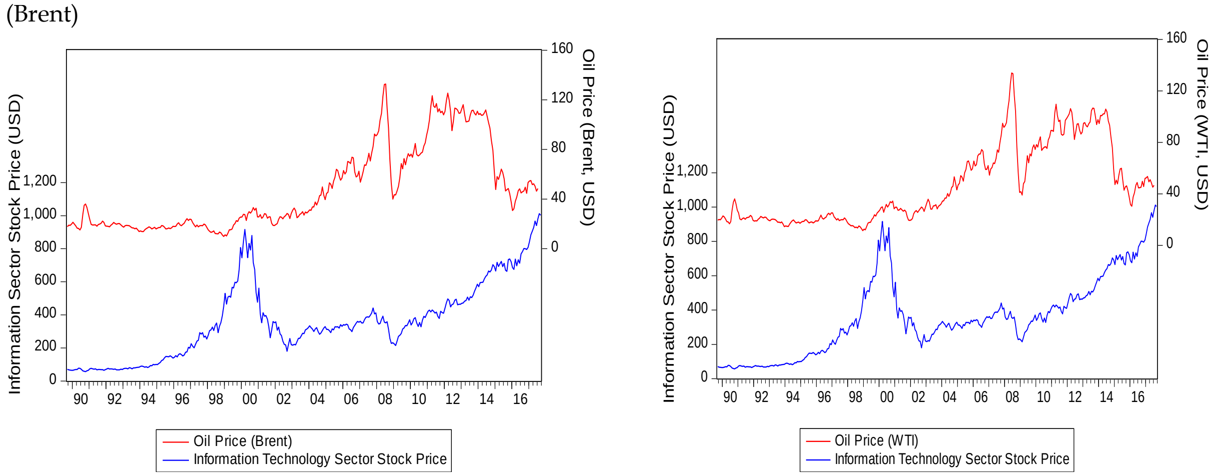


Fig. 4 Information Sector Stock Price and Oil Prices

Information Sector Stock Price and Word Oil Price (Brent) Information Sector Stock Price and Word Oil Price (Brent)



To glean insights from the nature and distribution of the series and to be properly guided in estimator selection, the descriptive statistics including mean, standard deviation, skewness and kurtosis are assessed. As in Table 2, the average oil prices (Brent and WTI) within the periods are very close at approximately 47USD and 46USD respectively. The standard deviations are close even though Brent seems to exhibit a higher volatility, skewness statistics are close to zero and positive, the kurtosis is also close to the threshold of 3.

Meanwhile, aggregate stock returns averaged 45%, an explicit assessment reveals less than half of all the sectors hover around this figure while more than half strictly deviate from the aggregate average. The financial, energy and material sector stock returns of 47%, 52% and 44%, respectively reflect the condition of the aggregate market compared to information, industry, telecommunication, consumer staples, consumer discretionary and health sector of 79%, 61%, 15%, 67%, 67% and 78% stock returns, respectively. All sectors have negative skewness in stock returns, an indication that returns are more usually negative than positive.

In Table 3, heteroscedascitity and serial correlation are assessed within the series. The ARCH-LM test for heteroscedasticity and the Q- and Q^2-Statistics for serial correlation are used. The tests are considered at 5, 10 and 20 lag lengths across the full sample. At lag 5, the result of the ARCH LM test rejects the null hypothesis of no autoregressive conditional heteroscedasticity in the series, although the evidences from the Q-Stat serial correlation tests seem inconclusive, the Q^2-Stat test doubtlessly affirms the presence of serial correlations in the series. At lag 10, consumer staples and health sector stock returns exhibit no conditional heteroscedasticity, even though the Q^2-Stat test continue to affirm the presence of serial correlations in the series. In addition, at lag 20, only energy sector stock returns concedes to the null hypothesis of no autoregressive conditional heteroscedasticity and serial correlation, other sectors' stock returns are significant.

Table 2: Descriptive Statistics

Variables	Mean	Standard Deviation	Skewness	Kurtosis
Oil Price				
Brent	47.31409	33.75446	0.886154	2.460284
WTI	46.38854	30.15439	0.810618	2.406816
Stock Price returns				
Aggregate	0.45829	5.41390	-0.61123	10.47122
Financial Sector	0.46980	6.27587	-0.94239	6.87337
Info Tech Sector	0.78979	7.10733	-0.63379	4.99957
Industry Sector	0.60560	4.91208	-0.71013	5.31706
Energy Sector	0.51685	5.23354	-0.23842	4.00629
Telecom Sector	0.15369	5.39629	-0.12547	5.13849
Material Sector	0.43681	5.64977	-0.36437	4.91581
Consumer Staples	0.67288	3.72463	-0.33537	4.68509
Health Sector	0.77812	4.41295	-0.35498	3.49552
Consumer Disc Sector	0.66662	4.99258	-0.48105	4.59075
Utilities Sector	0.31656	4.30485	-0.61305	4.02460

Source: Authors' computations

Thus, it can be inferred from Table 3 that whether at 5, 10 or 20 lag lengths, all sectors' stock returns but consumer staples, health and energy, agree to the presence of conditional heteroscedasticity and serial correlation.

Following the property checks on the data, it is crucial to also determine the degree of persistence in oil prices (the predictors) as well as any inherent endogeneity effect. In Table 4, the predictors (oil prices) exhibit persistence irrespective of sample size or sectoral stock involved, with the AR (1) estimated coefficients which seem to exhibit a high degree of persistence. The presence of endogeneity effect is also not in doubt where the relevant coefficients for virtually all the sectors including the aggregate are statistically significant at 1 percent level. In order to account for these data properties including conditional heteroscedasticity, we employ the FQGLS estimator of WN (2014) to estimate the predictability of oil price in the stock model. The results obtained from the FQGLS analyses are presented and discussed in the immediate succeeding section.

Table 3: Serial Correlation and Heteroscedasticity Tests

Lag Structure	Variables	Serial Correlation Test		Heteroscedasticity Test
	Oil Price	**Q-stat**	**Q-stat²**	**ARCH LM**
	Brent	1538.6***	1139.9***	1031.279***
	WTI	1504.6***	922.75***	777.8253***
	Stock Price			
	Aggregate	25.940***	261.67***	35.60068***
	Financial Sector	8.0127	143.74***	18.78130***
	Info Tech Sector	4.6831	147.06***	21.50297***
(5)	Industry Sector	5.0027	95.120***	12.57115***
	Energy Sector	2.0314	12.073**	2.091398*
	Telecom Sector	6.9807	67.890***	9.537534***
	Material Sector	0.8250	44.167***	8.868076***
	Consumer Staples	6.7203	15.831***	3.192984***
	Health Sector	10.217*	18.959***	2.883981**
	Consumer Disc Sector	6.9051	50.374***	6.410336***
	Utilities Sector	4.3998	53.064***	8.363415***
	Oil Price			
	Brent	2839.2***	1704.2***	506.8539***
	WTI	2726.9***	1149.9***	383.0948***
	Stock Price			
	Aggregate	32.330***	540.86***	28.08331***
	Financial Sector	18.676**	163.94***	9.832792***
	Info Tech Sector	9.0837	234.25***	12.58394***
	Industry Sector	14.054	105.72***	6.307623***
(10)	Energy Sector	4.3989	24.304***	1.956362**
	Telecom Sector	16.534*	113.88***	7.946232***
	Material Sector	10.777	58.875***	5.016295***
	Consumer Staples	12.478	17.300*	1.447256
	Health Sector	24.504***	20.419**	1.548003
	Consumer Disc Sector	9.8108	70.356***	4.133559***
	Utilities Sector	13.016	85.890***	4.944683***
	Oil Price			
	Brent	5054.8***	2184.4***	254.3149***

	WTI	4818.6***	1259.3***	187.6520***
	Stock Price			
	Aggregate	63.329***	820.48***	17.38812***
	Financial Sector	30.444*	169.20***	5.063442***
	Info Tech Sector	26.768	351.19***	7.616129***
	Industry Sector	22.051	124.71***	4.370445***
	Energy Sector	8.0495	28.212	1.253995
(20)	Telecom Sector	27.405	131.09***	4.116003***
	Material Sector	17.591	63.289***	2.744807***
	Consumer Staples	26.073	60.181***	2.343539***
	Health Sector	33.310**	57.864***	2.385431***
	Consumer Disc Sector	24.993	87.073***	2.403131***
	Utilities Sector	19.545	112.96***	2.722238***

Source: Authors' computations
Note: ***, ** and * denote 1, 5 and 10% levels of significance respectively

Table 4: Testing for persistence and endogeneity in the predictors (Oil Prices)

	Oil Prices			
	Persistence		**Endogeneity**	
Stock Prices	**Brent**	**WTI**	**Brent**	**WTI**
Aggregate	0.985673***	0.985929***	-0.556982***	-0.594901***
Consumer Disc	0.985673***	0.985929***	-0.703480***	-0.741898***
Consumer Staples	0.985673***	0.985929***	-0.677843***	-0.719602***
Energy	0.985673***	0.985929***	-0.762838***	-0.834412***
Finance	0.985673***	0.985929***	-0.328045**	-0.359304***
Health	0.985673***	0.985929***	-0.758540***	-0.809091***
Industries	0.985673***	0.985929***	-0.623314***	-0.666155***
Info Tech	0.985673***	0.985929***	-0.723623***	-0.772799***
Materials	0.985673***	0.985929***	-0.516681***	-0.552249***
Telecom	0.985673***	0.985929***	-0.026201	-0.024463
Utility	0.985673***	0.985929***	-0.347540***	-0.367502***

Source: Authors' computations

5.0 Discussion of Results

5.1 In-Sample Predictability

The starting point of our empirical investigation is to examine the asymmetric in-sample predictability of stock prices for both the aggregate and various sectors listed in Table 1 above. The results of the in-sample predictability are presented in Table 5. A snapshot of the table reveals that across all estimated models, there is a positive relationship between the two variables of interest. In essence, the positive shocks are positively signed, while the negative shocks carry negative coefficients. This assertion is valid for the two types of oil prices. The estimated coefficients are significant at 1 percent. The magnitudes of the negative shocks, in absolute terms, are higher than the positive shocks[8]. This implies that stock returns respond more the negative shocks than positive shocks. Studies whose results support our findings include Faff and Brailsford (1999), Aggarwal et al. (2012), Mohanty et al. (2013) and Moreno et al. (2017) among others. However, Broadstock et al. (2014), Kang et al. (2017) and Li et al. (2017) found conflicting results.

The theoretical underpinning of the relationship between oil price shocks and macroeconomic fundamentals, stock returns inclusive, is inconclusive. It could be summarily stated that the exact relationship between this nexus is dependent upon a host of factors such as: a firm being either a consumer or producer of oil (Mohanty et al. 2013); trade effect and its decompositions (Raheem, 2017); a decline in the global oil production/supply (Kilian, 2009). It is also argued that the exact effect of oil price shock is industry-, time period-, oil price- specific (Arouri, 2011; Scholtens and Yurtseve, 2012 and Pinho and Madaleno, 2016). To a large extent, relevant empirical studies confirm the blurry theoretical arguments, by showing lack of consensus in their results.

At the US industry level, most studies have examined the nexus using transport and oil and gas sectors. The general position of these studies is that the selected industries respond only to positive oil price shock. Our study further advances this general conclusion in two dimensions (i) asymmetry is not only limited to the oil and gas and transport sectors, but the entire sector of the economy; (ii) while acknowledging that positive shock have significant than on stock returns, the effect of the negative shock outweighs the positive.

[8] However, the consumer discretionary sector reveals otherwise. This might not be unconnected to the fact that the sector is regarded as a non-essential to the daily activities of the economic agents.

Table 5: In-sample predictability of oil–stock nexus

Stock	Brent		WTI	
	positive shock	negative shock	positive shock	negative shock
Aggregate	0.2508***	-0.282***	0.284***	-0.320***
	(0.013)	(0.013)	(0.015)	(0.014)
Financial Sector	0.331***	-0.378***	0.085***	-0.096***
	(0.014)	(0.013)	(0.010)	(0.011)
Info Tech Sector	0.380***	-0.430***	0.432***	-0.491***
	(0.027)	(0.028)	(0.029)	(0.032)
Industry Sector	0.247***	-0.276***	0.279***	-0.314***
	(0.012)	(0.012)	(0.013)	(0.012)
Energy Sector	0.191***	-0.211***	0.216***	-0.239***
	(0.008)	(0.008)	(0.008)	(0.009)
Telecom Sector	0.140***	-0.169***	0.161***	-0.193***
	(0.019)	(0.020)	(0.021)	(0.022)
Material Sector	0.103***	-0.120***	0.118***	-0.137***
	(0.009)	(0.008)	(0.009)	(0.009)
Consumer Staples	0.220***	-0.251***	0.249***	-0.285***
	(0.012)	(0.011)	(0.013)	(0.011)
Health Sector	0.327***	-0.366***	0.369***	-0.415***
	(0.014)	(0.013)	(0.015)	(0.015)
Consumer Disc	0.244***	-0.227***	0.275***	-0.314***
Sector	(0.012)	(0.011)	(0.012)	(0.011)
Utilities Sector	0.075***	-0.084***	0.085***	-0.095***
	(0.001)	(0.010)	(0.010)	(0.011)

Source: Authors' computation.
Note: Values in parenthesis represent the standard error statistics, while *** signifies the level of statistical significance at 1 percent.

5.2 In-Sample Forecast Evaluation

The in-sample predictability results presented in the immediate preceding section offer an insight that the various sectoral stocks in the US economy respond asymmetrically to changes in oil prices. There is the need to examine the accuracy of the forecast performance of the two predictors. The forecast performance is evaluated using the Root Mean Square Error (RMSE), the Campbell-Thompson test and the Diebold-Mariano test for robustness.

The results for the in-sample forecast evaluation using the Campbell-Thompson test are presented in Table 6. For both oil price proxies, the statistics are consistently negative for all the sectors. Since the reference predictor is the positive oil price changes; it then implies that the predictive model with the negative oil price changes outperforms the positive variant. This further validates the in-sample predictability results reported in Table 5 where negative oil price changes exert greater effects on stock prices than the positive oil price changes. The next line of scientific investigation is to determine the level of statistical significance of the difference between the forecast of the two predictors. This action is actualized through the use of Diebold and Marino Test as presented in Table 7. The idea is to further ascertain whether the difference in the forecast performance of the two predictors is statistically significant. The null hypothesis is that the difference is not significant suggesting equality of forecast accuracy between the two predictors. There is overwhelming evidence for us to reject the null hypothesis for the 10 sectors under consideration. In other words, the superior forecast performance of the negative oil price changes over the positive variant is statistically significant. This also suggests that economic agents particularly investors in the US stock market respond more to negative oil price shock. Such behaviour therefore should be exploited when forecasting the behaviour of the US stock market in order to produce more accurate forecast results. Put differently, ignoring such information when forecasting US stock market may produce less desirable results.

Table 6: In- and Out-of-Sample forecast performance using Campbell-Thompson test

Predictor	**Brent**				**WTI**			
	In-Sample	Out-of-Sample			In-Sample	Out-of-Sample		
		H=12	H=24	H=36		H=12	H=24	H=36
Aggregate	-0.107	-0.114	-0.157	-0.207	-0.110	-0.123	-0.175	-0.223
Financial Sector	-0.204	-0.208	-0.255	-0.317	-0.020	-0.027	-0.032	-0.039
Info Tech Sector	-0.051	-0.061	-0.101	-0.137	-0.051	-0.667	-0.144	-0.155
Industry Sector	-0.126	-0.134	-0.180	-0.238	-0.131	-0.144	-0.199	-0.268
Energy Sector	-0.052	-0.065	-0.021	0.065	-0.052	-0.067	-0.017	0.079

Telecom Sector	-0.03	-0.028	-0.040	-0.048	-0.038	-0.034	-0.047	-0.059
Material Sector	-0.102	-0.101	-0.095	-0.075	-0.112	-0.111	-0.103	-0.081
Consumer Staples	-0.168	-0.167	-0.199	-0.245	-0.180	-0.182	-0.222	-0.277
Health Sector	-0.113	-0.133	-0.193	-0.253	-0.108	-0.136	-0.210	-0.280
Consumer Disc Sector	-0.182	-0.181	-0.223	-0.274	-0.190	-0.193	-0.245	-0.307
Utilities Sector	-0.023	-0.029	-0.034	-0.039	-0.019	-0.027	-0.033	-0.039

Note: The positive asymmetry is used as the reference predictor. Thus, a positive statistic implies that the positive shock outperforms the negative while the reverse holds if the statistic is negative.

Table 7: In- and Out-of-Sample forecast performance using Diebold & Mariano test

Predictor	Brent				WTI			
	In-Sample	Out-of-Sample			In-Sample	Out-of-Sample		
		H=12	H=24	H=36		H=12	H=24	H=36
Aggregate	-4.267*** (0.000)	-4.980*** (0.000)	-6.254*** (0.000)	-7.370*** (0.000)	-4.266 (0.000)	-5.272*** (0.000)	-6.463*** (0.000)	-7.477*** (0.000)
Financial Sector	-5.080*** (0.000)	-5.743*** (0.000)	-6.932 (0.000)	-7.977*** (0.000)	-2.342** (0.019)	-3.434*** (0.000)	-4.202*** (0.000)	-4.935*** (0.000)
Info Tech Sector	-2.628*** (0.008)	-3.482*** (0.000)	-4.951*** (0.000)	-6.233*** (0.000)	-2.620*** (0.000)	-3.683*** (0.000)	-5.114*** (0.000)	-6.376*** (0.000)
Industry Sector	-4.694*** (0.000)	-5.531*** (0.000)	-6.723*** (0.000)	-7.783*** (0.000)	-.898*** (0.000)	-5.880*** (0.000)	-6.975*** (0.000)	-7.864*** (0.000)
Energy Sector	-2.333** (0.019)	-3.040*** (0.002)	-0.830 (0.406)	-2.035** (0.042)	-2.249** (0.024)	-3.062*** (0.002)	-0.629 (0.528)	-2.276** (0.023)
Telecom Sector	-2.627*** (0.009)	-2.587*** (0.009)	-3.763*** (0.000)	-4.916*** (0.000)	-3.065*** (0.000)	-3.307*** (0.000)	-4.655*** (0.000)	-5.944 (0.000)
Material Sector	-4.981*** (0.000)	-4.919*** (0.000)	-4.628*** (0.000)	-3.612*** (0.000)	-5.062*** (0.000)	-4.984*** (0.000)	-4.631*** (0.000)	-3.569*** (0.000)
Consumer Staples	-5.507*** (0.000)	-6.082*** (0.000)	-7.291*** (0.000)	-8.294*** (0.000)	-5.731*** (0.000)	-6.430*** (0.000)	-7.584*** (0.000)	-8.391*** (0.000)
Health Sector	-3.389*** (0.000)	-4.457*** (0.000)	-5.709*** (0.000)	-6.727*** (0.000)	-3.258*** (0.001)	-4.487*** (0.000)	-5.715*** (0.000)	-6.699*** (0.000)
Consumer Disc Sector	-4.806*** (0.000)	-5.349*** (0.000)	-6.597*** (0.000)	-7.667*** (0.000)	-5.002*** (0.000)	-5.682*** (0.000)	-6.921*** (0.000)	-7.822*** (0.000)
Utilities Sector	-2.697*** (0.007)	-3.795*** (0.000)	-4.516*** (0.000)	-5.152*** (0.000)	-2.342** (0.019)	-3.433*** (0.000)	-4.202*** (0.000)	-4.935*** (0.000)

Source: Authors' Computation.

Note: The test-statistic for the Diebold and Mariano test follows a Student's *t-distribution* with *T-1* degrees of freedom. The corresponding p-value is reported in parenthesis and ***, **, and * imply levels of statistical significance at 1, 5 and 10% respectively.

5.3 Out-of-Sample Forecast Evaluation

So far, the study has been able to provide evidence of the significant asymmetric predictability between stock and oil price for the US economy. Next to this is to inquire about the out-of-sample forecast performance of the predictors. On the basis of the in-sample predictability and in-sample forecast performance, we find evidence of asymmetric relationship and more importantly, the negative oil asymmetry produces more accurate forecast than the positive oil price asymmetry. Since the evidence from the in-sample forecast evaluation may not necessarily translate into out-of-sample forecast, it then becomes imperative to extend our forecast evaluation to include the latter for completeness. By this, we want to examine if the results obtained for the in-sample can be replicated for the out-of-sample.

For this exercise, we use the second half of the full sample (50 per cent) for the out-of-sample forecast evaluation and multiple forecast horizons are considered for robustness. Thus, the out-of-sample forecasts are produced for 12-month (h=12), 24-month (h=24) and 36-month (h=36) ahead forecasts. The results are reported in Tables 6 and 7. Like the in-sample case, we employ both the Campbell-Thompson and Diebold and Mariano tests to evaluate the forecast performance.

On the aggregate, there seems to be no significant difference between the results of the in-sample and out-of-sample. In other words, the relationship that exists in the oil-stock model is more likely to be sustained even beyond the estimation period. Using the Campbell-Thompson test, like the in-sample results, the statistics turn up to be negative consistently for all the sectors with the exception for energy which is only positive at the 36-month ahead forecast. Similarly, the Diebold-Mariano test suggests unequal forecast accuracy between the positive and negative oil price asymmetries. Thus, the negative oil price changes produce more accurate out-of-sample forecasts for US stocks than the positive oil price changes particularly for 12-month and 24-month forecast horizons. Information about the exposure of US stocks to oil price risk is important for hedging effectiveness more so that the response of the stocks is found to be asymmetric. Thus, in the formulation of hedging weights and ratios, it may be necessary to build such information into the framework for a more robust outcome.

5.4 Simple average combination forecast vs Individual forecasts

Up until this point, we have been able to present evidence suggesting that the asymmetric predictability of oil price in the US stock model cannot be ignored. In fact, the evidence is established for both the in-sample and out-of-sample forecasts. In essence, the forecast performance of the stock model differs between positive and negative oil price asymmetries with the latter showing a better forecast performance. Meanwhile, Timmermann (2006, 2013) and others have suggested a combination forecast test to see if combining the forecasts of both predictors will outperform their individual forecasts. Recall that in the previous analyses, we evaluate singly the forecast performance of the predictors. Thus, we now extend these analyses to include the combination forecast using the simple average approach. Thereafter, we compare the combined forecasts for the individual stocks with those of the positive and negative oil price changes. The results are presented in Table 8.

Overall, the forecast of the negative oil price changes seems to outperform both the positive and the combined forecasts. This position is valid for both the in-sample and out-of-sample forecast. The only exception is the energy sector which reveals mixed results for the out-of-sample forecast. It is shown that for the 24-month forecast, the simple average of the two forecasts (based on 24-month) outweighs the individual forecasts.

Table 8: Combination Forecasts using simple average of RMSE

	Brent				WTI			
	In-sample	Out-of-Sample			In-sample	Out-of-Sample		
		H=12	H=24	H=36		H=12	H=24	H=36
Aggregate	0.242^n	0.255^n	0.253^n	0.267^n	0.226^n	0.237^n	0.247^n	0.256^n
Financial Sector	0.229^n	0.235^n	0.247^n	0.257^n	0.182^n	0.191^n	0.187^n	0.181^n
Info Tech Sector	0.470^n	0.496^n	0.5529^n	0.563^n	0.461^n	0.488^n	0.520^n	0.554^n
Industry Sector	0.206^n	0.213^n	0.215^n	0.218^n	0.199^n	0.206^n	0.208^n	0.212^n
Energy Sector	0.153^n	0.152^n	0.153$^\wedge$	0.159^p	0.150^n	0.149^n	0.151^n	0.156^p
Telecom Sector	0.349^n	0.384^n	0.409^n	0.430^n	0.347^n	0.381^n	0.407^n	0.427^n
Material Sector	0.154^n	0.149^n	0.146^n	0.145^n	0.149^n	0.145^n	0.141^n	0.141^n
Consumer Staples	0.194^n	0.198^n	0.205^n	0.213^n	0.185^n	0.191^n	0.198^n	0.206^n
Health Sector	0.269^n	0.257^n	0.280^n	0.306^n	0.237^n	0.252^n	0.274^n	0.299^n
Consumer Disc Sector	0.191^n	0.197^n	0.202^n	0.214^n	0.185^n	0.191^n	0.196^n	0.207^n
Utilities Sector	0.183^n	0.192^n	0.187^n	0.182^n	0.182^n	0.191^n	0.189^n	0.181^n

Note: These statistics represent the composite forecast results involving both the positive and negative changes in oil prices. The asterisk (^) indicates that the combination forecast outperforms the individual forecasts while the superscript 'p' and 'n', respectively denote that the positive changes and negative changes outperform other forecasts including the combined forecasts.

5.5 Robustness Test

The robustness test involves the two proxies commonly used in the literature are Brent and WTI prices. The essence of the robustness tests is to examine the sensitivity or otherwise of our results to variable measurements. It is observed that our results in relation to sign and significance are robust to the two measures of oil price. The robustness of the results is also attested to by the in-sample and out-of-sample forecasts. In other words, regardless of the measure of oil price, the conclusion of our analyses remains the same.

6.0 Conclusion

Energy is central to the growth process of modern economies and hence the role of oil is pivotal in many sectors of economy. The study considers the role of oil price shocks in the predictive model of stock prices. We attempt to improve on existing studies by exploring the inherent characteristics of the variables of interest. Thus, we account for asymmetry, persistence, endogeneity and conditional heteroscedasticity in the stock-oil nexus. We compiled dataset for both the aggregate and sectoral stock prices for the US economy. We evaluate the predictability of the asymmetric stock models for both the in-sample and out-of-sample forecasts based on the frameworks of Lewellen (2004) and Westerlund and Narayan (2012, 2014). In addition, we utilised the first half of the full sample (50 per cent) for in-sample analyses while the second half is reserved for the out-of-sample forecast evaluation. The latter is conducted for 12-period, 24-period and 36-period ahead forecast horizons.

The results of the in-sample predictability model reveal that sectoral US stocks respond asymmetrically to oil price changes. This finding is further strengthened by the Diebold and Mariano test suggesting that the forecast accuracy between positive and negative oil price changes is unequal. More specifically, the negative variant consistently outperforms the positive variant. These findings are evident for both the in-sample and out-of-sample forecast regardless of the forecast horizon. In addition, we consider the composite forecast evaluation which sheds light as to whether the combined forecasts of the asymmetric predictive oil price models will outperform the individual forecasts. The results show that the negative shock also outperforms the combined forecasts involving the two predictors. These results are consistent for both the in-sample and out-sample analyses and are also robust to changes in the measure of oil prices.

Overall, economic agents operating in the US stock market tend to respond more to negative oil price shock than the positive and therefore, financial analysts and investors seeking to maximize returns may need to exploit this behaviour of economic agents in order to produce a more accurate forecast for the US stock market. In addition, this information will be useful in the computation of hedging weights and hedging ratios for stocks in the presence of oil risk. More importantly, accounting for the role of asymmetries in the oil-stock model may enhance hedging effectiveness.

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